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Financial applications of machine learning: A literature review

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A R T I C L E I N F O

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A B S T R A C T

This systematic literature review analyses the recent advances of machine learning and deep learning in finance. The study considers six financial domains: stock markets, portfolio management, cryptocurrency, forex markets, financial crisis, bankruptcy and insolvency. We provide an overview of previously proposed techniques in these areas by examining 126 selected articles across 44 reputed journals. The main contributions of this review include an extensive examination of data characteristics and features used for model training, evaluation of validation approaches, and model performance addressing each financial problem. A systematic literature review methodology, PRISMA, is used to carry out this comprehensive review. The study also analyses bibliometric information to understand the current status of research focused on machine learning in finance. The study finally points out possible research directions which might lead to new inquiries in machine learning and finance.

1. Introduction

Machine learning is a powerful branch of Artificial Intelligence that has widespread applications in banking and finance. It enables financial institutions to detect fraudulent transactions, and assists managers in credit scoring, ranking and granting decisions. Financial Robo-advisors and chatbots provide banking assistance to clients, asset allocation systems provide risk-return assessments to investors whilst automated insurance services are available to policyholders; the financial applications of Machine learning are interminable. With its ability to process massive quantities of data and simultaneously accommodate non-linearities in data, Machine learning has emerged at the forefront of statistics. Recent decades have witnessed a great deal of research using computational intelligence in finance (Ozbayoglu, Gudelek, & Sezer, 2020). The present study compiles and reviews the recent advancements of Machine learning in six financial areas: stock markets, portfolio management, forex markets, bankruptcy and insolvency, financial crisis, and cryptocurrency. It examines the models: k-Nearest Neighbours, Bayesian classifiers, decision trees, Random Forest, Support Vector Machine, Deep learning models such as Artificial Neural Network/Deep Neural Network, Feed Forward Neural Network, Back Propagation Neural Network, Multilayer Perceptron, Convolutional Neural Network, Recurrent Neural Network, Long Short-Term Memory, Gated Recurrent Units, Reinforcement learning models, hybrid and ensemble models; and identifies its appropriate applicability in specific fields to solve various financial problems.

2. Related work

Over the last three decades, several review articles have been published in finance, banking, business, and allied fields. While many review articles focused only on a single financial application, particularly surveys on stock market prediction (Kumbure, Lohrmann, Luukka, & Porras, 2022), a few encompassed multiple areas of finance. These

Abbreviations: BPNN, Back Propagation Neural Network; CAC 40, Cotation Assistée en Continu; CCI, Commodity Channel Index; CSI, China Securities Index; DBN, Deep Belief Network; EBITDA, Earnings Before Interest, Tax, Depreciation and Amortization; ELM, Extreme Learning Machine; ESG, Environmental Social Governance; ESRB, European Systemic Risk Board; FDIC, Federal Deposit Insurance Corporation; FFNN, Feed Forward Neural Network; FLF, Firefly Algorithm; HSI, Hang Seng Index; HYS3, Hybrid Supervised Semi-Supervised; ibexIBEX, IBerian IndEX, Spain; ISFL, Improved Shuffled Frog Leaping; MCC, Matthew's Correlation Coefficient; MDD, Maximum Drawdown; MRB, Modified Renko Bars; NMSE, Normalised Mean Squared Error; RBNN, Radial Based Neural Network; RMSRE, Root Mean Squared of Relative Error; PLS, Partial Least Squares; ROC, Receiver Operating Characteristic; LDA/QDA/MDA, Linear/Quartile/Multi Discriminant Analysis.

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studies include Computational Intelligence or AI as a whole and not explicitly Machine learning as a subset; for example, Pulakkazhy & Balan (2013) reviewed the applications of data mining in banking; Aguilar-Rivera and Valenzuela-Rendón & Rodríguez-Ortiz (2015) surveyed the applications of Genetic Algorithm & the Darwinian approach in finance. Table 1 summarises these related surveys, including the study period, keywords, number of surveyed articles, financial applications, and computational methods. This study thus aims to provide a consolidated and systematically arranged review of recent literature using the standard PRISMA method. This review serves as a one-stop solution for researchers at the intersection of Machine learning and finance.

Emerson, Kennedy, O'Shea, & O'Brien (2019) review 55 articles on portfolio construction, return forecasting, and risk modelling; Nosratabadi et al. (2019) review articles on the stock market, cryptocurrency, e-commerce, marketing, and corporate bankruptcy prediction; using Machine learning. Rundo, Trenta, & di Stallo (2019) and Cavalcante, Brasileiro, Souza, Nobrega, & Oliveira (2016) cover several aspects of financial markets where Machine learning models and Computational Intelligence are applied. However, it lacks an in-depth investigation into the accuracy of the model. Amongst the studies exclusively based on deep learning, Huang, Chai, & Cho (2020) reviewed credit risk prediction, macroeconomic prediction, exchange rate prediction, stock market prediction, oil price prediction, portfolio management, and stock trading. Ozbayoglu, Gudelek, & Sezer (2020) review 144 articles across algorithmic trading, risk assessment, fraud detection, portfolio management, asset pricing and derivatives market, cryptocurrency and blockchain studies, financial sentiment analysis and behavioural finance, financial text mining, theoretical/conceptual studies, and studies with other financial applications. These researchers critique deep learning models or the applications of neural networks in finance; however, keeping mum over other Machine learning models.

Surveys on neural network applications in finance date back to the 1990s (Hawley, Johnson, & Raina, 1990) and continue to be surveyed for its ever-evolving applications in finance (Riyazahmed, 2021). While most of these surveys are exclusive to neural networks (Wong, Bodnovich, & Selvi, 1997, Wong & Selvi, 1998, Vellido, Lisboa, & Vaughan, 1999) (Fadlalla & Lin, 2001, Tkác & Verner, 2016)) and deep learning ((Ozbayoglu, Gudelek, & Sezer, 2020, Huang, Chai, & Cho, 2020)), a few are on AI ((Bahrammirzaee, 2010, Cao, 2020)). Wong, Bodnovich & Selvi (1997) presented 213 applications of neural networks in business across 203 articles, and Wong & Selvi (1998) presented 37 applications in finance from 66 articles. However, a discussion on these financial applications in relevance to the models used does not form part of the work. Similarly, Vellido, Lisboa & Vaughan (1999) identify the use of neural networks in business across the areas of accounting, auditing, finance, marketing, management, and production; but discuss only bankruptcy prediction, credit evaluation, and market segmentation. The findings of most surveys are categorized on the models used but not based on their basis financial applicability. Thus, the present study aims to classify the state-of-the-art machine learning techniques based on their financial applications (*Sec* 4.1 to 4.6).

The review is systematically organised using the standard PRISMA method. As part of its main contribution, it explores the characteristics of data and most frequently used features to train the models. We examine the machine learning and Deep Learning models applied in finance, and obtain state-of-the-art relevant models. Based on the most frequently used performance metrics, we evaluate the performance of models addressing each financial problem. In addition, the study includes an application-model analysis, performance metrics map, analysis of software/programming languages, and validation approaches employed. Through an analysis of bibliographic information, this study also aims to gain an understanding of the current state of the published research focused on machine learning in finance. The study will serve as a source of reference to researchers and also for practical usage.

The paper is organized as follows: section 2 presents the related work, and section 3 describes the main procedure of the search and methodology for developing the base of the study. Section 4 consists of a review of the features, different machine learning models employed in various financial applications, and an evaluation of performance metrics. An analysis of the literature reviewed and bibliographic information is presented in Section 5. Section 6 provides the study's conclusion and limitations. Section 7 highlights the lessons learned and directions for future research.

3. Methodology

Using of a standard methodology for conducting a review not only supports the quality of the review but also allows researchers to replicate the review study. Given this, the study adopts the PRISMA standard for conducting the review process (Ardabili, Abdolalizadeh, Mako, Torok, & Mosavi, 2022). PRISMA stands for Preferred Reporting Items for Systematic Reviews and meta-Analyses. Since the study examines a single database, sparse adjustments were required, as explained in the following stages.

3.1. Identification

Being a review study, similar and related articles in the field of Computational Intelligence and AI in finance were collected and categorized. We identified the current trends of work, research gaps, and keywords that most currently occur in the field of machine learning. Using Google Scholar search engine for research material provided millions of results, most of which are irrelevant or unrelated to the objective. Surveys in this area extract articles from multiple databases, namely Springer Link, ACM Digital Library, ScienceDirect, Taylor and Francis Online, EBSCOhost, and more; however, they need to review articles based on a single database comprehensively. ScienceDirect is a common database selected by previous review articles. As such, articles for this study have been sourced solely from ScienceDirect database, which provides access to a wide range of publications in diversified fields.

The advanced search strategy was adopted to filter the articles included in the title, abstract or author-specified keywords since 2015, details of which are provided in Table 2. After multiple checks, the keywords selected for this study were arrived at to include the most relevant articles. These include "Machine learning" OR "Deep learning" OR "Neural networks" OR "Support vector machine" OR "LSTM" OR "Decision tree" OR "Random Forest" in combination with the Boolean operator AND "Finance" OR "Banking" OR "Investment" OR "Stock market" OR "Cryptocurrency" OR "Insolvency" OR "Bankruptcy" OR "Forex" OR "Foreign exchange" OR "Financial crisis" OR "Financial Distress" OR "Market crash" OR "Currency crisis" OR "Sovereign debt". One of the major problems identified in this database was the limitation to a maximum of 8 Boolean connectors. This required multiple search executions using the advanced search strategy, thereby collecting duplicative articles from the same database. This search strategy resulted in 1512 articles that went through further screening.

3.2. Screening

This stage aims to eliminate those articles that are duplicative and irrelevant to this review. The limitation on the number of Boolean connectors led to 463 duplicative articles entering the screening stage. When we examined the relevance of the remaining articles by reading the title and abstract, we found several articles that do not fall under the purview of finance. This was due to search queries having multiple meanings; for example, while we refer to "investment" in monetary terms, authors have synonymously used it to imply commitment or dedication of one's time, efforts, or other resources. Hence, ample irrelevant articles were included, which needed elimination. Also, articles that did not employ a model related to one of the mentioned financial domains using machine learning methods were eliminated. Out

Table 1
Summary of related surveys.

Authors	Study Period	Keywords	No. of Articles	Financial areas	Computational method
Hawley, Johnson & Raina (1990)	N/A	N/A	N/A	Corporate finance: financial simulation, prediction, evaluation, credit approval, financial institutions: assessing bankruptcy risk, security/asset portfolio management, pricing IPOs, Professional investors: identification of arbitrage opportunities, technical analysis, fundamental analysis	Neural Networks
Wong, Bodnovich & Selvi (1997)	1988–95	Neural Network and Neural Networks	203	213 applications across accounting/auditing, Human resources, Information systems, Marketing/distribution, Production/operations and Others	Neural Networks
Wong & Selvi (1998)	1990–96	Neural Network and Neural Networks	66	37 applications in finance	Neural Networks
Vellido, Lisboa & Vaughan (1999)	1992–98	N/A	N/A	Accounting and Auditing, Finance Management, Marketing, Production, Others: Bankruptcy prediction, credit evaluation and market segmentation discussed in detail	Neural Networks
Fadlalla & Lin, (2001)	1986–97	Neural networks, current liabilities bankruptcy, bonds, stocks, current assets, loans, equity, credit, quick assets, assets, liability, owner's equity	40	Bankruptcy Prediction, Stock market forecasting, Credit analysis, Underwriting analysis and Business cycle recognition	Neural Networks
Bahrammirzaee (2010)	1990–2010	N/A	N/A	Credit evaluation, Portfolio management, Financial Prediction and Planning	AI
Pulakkazhy & Balan (2013)	N/A	N/A	N/A	Risk Management and Default Detection, Marketing, Fraud Detection, Money Laundering Detection, Investment Banking	Data mining
Aguilar-Rivera, Valenzuela-Rendón, & Rodríguez-Ortiz (2015)	N/A	N/A	N/A	Abnormal noise and fraud detection, Arbitrage, Bankruptcy detection, Cash management, Credit Portfolios, Credit scoring, Fundamental Analysis, Forecasting, Index tracking, Market simulations, Procurement, Portfolio optimization, Trading and Trading Execution	Genetic Algorithm and Darwinian Approach
Cavalcante, Brasileiro, Souza, Nobrega, & Oliveira (2016)	2009–15	Financial markets, stock markets, neural networks, portfolio, financial time series, forecasting, machine learning, comparative study, fuzzy systems computational intelligence, support vector machines, extreme learning machines, text mining, feature selection, novelty detection, clustering, survey, review	N/A	Several topics in financial markets. Not categorised from a financial perspective	Computational Intelligence
Tkác & Verner (2016)	1994–15	Neural networks and business, finance, corporate, accounting, stocks, capital, costs, financial analysis, bankruptcy, exchange rates, financial distress, inflation, marketing, customers and bonds	412	Accounting and Auditing, Costs monitoring Credit scoring, Customer metrics Derivatives, Distress & bankruptcy, Decision support, Exchange & interest rates, financial analysis, Fraud analysis, Inflation, Marketing, Reviews, Sales, Shares and bonds	Neural Networks
Rundo, Trenta, & di Stallo (2019)	N/A	N/A	N/A	Several topics in financial markets. Not categorised from a financial perspective	Machine Learning
Emersonet al. (2019)	2015 onwards	Portfolio management, risk management, stock market forecasting with machine learning	55	Portfolio Construction, Return Forecasting and Risk Modelling	Machine Learning
Cao (2020)	N/A	N/A	N/A	Modelling economic-financial mechanisms, Financial market analysis and forecasting, Agent-based economics and finance, Intelligent investment, optimization and management, Optimal operations, governance and regulation, Intelligent credit, loan and risk management, Intelligent marketing analysis, Global cross-market analysis, campaign and customer care, Intelligent online, IoT-based and Internet finance, Intelligent blockchain, Smart alternative economic-financial products and services	AI
Huang, Chai, & Cho (2020)	2014–18	Deep Learning, RNN, LSTM, Reinforcement Learning, Finance, Market risk, Stock risk, Credit risk, Stock market, Banking	40	Banking and Credit: Credit Risk Prediction, Macroeconomic Prediction, Financial Market Investment: Exchange Rate Prediction, Stock Market Prediction, Oil Price Prediction, Portfolio Management and Stock trading	Deep Learning
Ozbayoglu, Gudelek, & Sezer (2020)	Published last 5 years ago	Deep Learning and others	144	Algorithmic Trading, Risk Assessment, Portfolio Management Fraud Detection, Asset Pricing, Derivatives Market, Crypto Currency & Blockchain studies, Financial Sentiment Analysis & Behavioural Finance, Financial Text Mining, Theoretical/Conceptual Studies and Other Financial Applications	Deep Learning
Nosratabadi, et al (2020)	N/A	Machine learning and deep learning	57	Stock market, Marketing, Cryptocurrency, e-commerce and corporate bankruptcy prediction	Machine Learning
Riyazahmed (2021)	N/A	Neural Networks and Finance	51	Investment prediction, Credit evaluation, financial distress and other financial applications	Neural Networks

Source: Author's compilation.

Table 2
Applied filtering options during the search process.

Filtering options	Specification
Published year	2015 Onwards
Document type	Journal only
Language	English
Published stage	Final
Text availability	Full texts available

Source: *Author's compilation.*

of 1512 articles, a total of 1136 duplicative and irrelevant articles were eliminated, and 376 went through for an eligibility check.

3.3. Eligibility

In this stage, the authors read the full text of the articles to determine those that are eligible for review. Thus, the eligibility stage involved further filtering of articles determined by the inclusion and exclusion criteria designed for the selection of the most relevant articles:

Inclusion criteria

- Utilizing machine learning or hybridized models that combine machine learning and other statistical tools or ensemble or deep learning models
- Studies that compare machine learning models to non-machine learning models exclusively in finance
- Studies that are published exclusively in English

Exclusion criteria

- Other subsets of AI and Computational Intelligence
- Studies that do not provide adequate details of the machine learning model utilized
- Conference articles, review papers, book chapters

Each article was carefully filtered based on the criteria mentioned above, ultimately selecting 126 relevant articles.

3.4. Inclusion

The final stage includes creating a database for qualitative and quantitative analysis. The current study comprises 126 articles, all of which are analysed to create the database. Contents of the selected articles were classified based on their financial domains and were systematically arranged (See Table 3). Details of title of the article, name and number of author(s), year of publication, name of the publishing journal, author-specified keywords, machine learning models employed, performance metrics, validation methods, and other relevant information pertaining to each of the above-mentioned financial applications were obtained.

Table 3
Number of articles reviewed across financial domains.

Financial Domain	Number of articles
Stock Market	41
Portfolio Management	14
Cryptocurrency	19
Foreign Exchange Market	17
Financial Crisis	11
Bankruptcy and Insolvency	24
TOTAL	126

Source: *Author's compilation.*

4. Review of financial applications of machine learning

This section presents a comprehensive review of existing literature across the six financial areas: stock markets, portfolio management, cryptocurrency, foreign exchange markets, financial crisis, and bankruptcy and insolvency. The performed review of the 126 selected articles includes an analysis and discussion on the features, datasets, and models used to address each financial problem.

Furthermore, Tables 4.1–4.6 display the models, time period, performance metrices and necessary information regarding each financial domain.

4.1. Stock market prediction

Predicting the stock market continues to be an interesting yet challenging area of research due to the financial time series being noisy, chaotic, and non-stationary. Despite the Efficient Market Hypothesis theory, which suggests that it is impossible to outperform the market, yet with development in technology, analysts can closely predict the stock market, which can help traders gain monetary benefits. Understanding the stock market and its innumerable interconnected factors has gained the attention of investors and researchers. A wide range of factors, including global interactions in foreign investments, exchange rates, political turmoil, natural calamities, company, and management-related changes, financial news, inflation, market sentiments, and social moods of the people, can affect the stock market. Nevertheless, knowing these factors and guesstimating their impact on the stock market is insufficient. There is a need to incorporate these factors into a predictive model by converting the available data into valuable features, which are significant attributes of machine learning and deep learning models. Their contribution in the area of financial time series prediction is overwhelming. The stock market time series being noisy and volatile has proved to be a test of robustness to determine the performance of these machine learning models. Based on the literature reviewed, the financial application of machine learning is predominant in stock market forecasting (41 out of 126 papers), which will be the principal theme of this section. Table 4 summarises the details of these articles highlighting the stocks/indices for prediction, the type of features employed for training, the predictive model, study period, and software tools.

Research in this area encloses forecasting of stock prices, stock returns, stock volatility, market index values, and binary classification of the direction of stock movement. While most studies focus on predicting the next day's closing price or return for a stock or index, a few focus on intraday price prediction (Chong, Han, & Park, 2017) (Sun, Xiao, Liu, Zhou, & Xiong, 2019). Beyond stock market forecasting, the state-of-the-art machine learning models also apply to other stock market-related aspects, such as: measuring the impact of factors influencing the stock market (Khattak, Ali, & Rizvi, 2021), determining the financial immunity of countries to the COVID-19 pandemic (Zaremba, Kizys, Tzouvanas, Aharon, & Demir, 2021), developing mobile application frameworks to alert potential investors on possible market close prices, and develop trading strategies (Chandra & Chand, 2016).

4.1.1. Features and datasets for stock market prediction

A taxonomy proposed by Bustos & Quimbaya (2020) classifies the predictive features into structured and unstructured data. While the structured data comprises market information, technical indicators, and economic indicators, the unstructured data consists of news, social networks, and blogs. This study adopts the same pattern for analysing the features for stock market prediction.

In the words of Fama (1965): "To what extent can the past history of a common stock's price be used to make meaningful predictions concerning the future price of the stock?" Historical stock market information in the form of open, close, high, low prices, and volume traded are most commonly used to predict the stock market, either individually or in combination with other structured and unstructured data (see

Table 4
Financial application of machine learning in stock market prediction.

Authors	Index/Stock, Country	Model	Time Period	Performance evaluation	Task
Chandra & Chand (2016)	*ACI* Worldwide, Staples Inc., and Seagate Technology Holdings at NASDAQ, US	RNN > FFNN	December 2006 to October 2010	RMSE = 0.0191, 0.0218, and 0.169 for the respective stocks	Forecasting
Qiu, Song & Akagi (2016)	Nikkei 225 index, Tokyo Stock Exchange, Japan	ANN	November 1993 to July 2013	MSE = 0.0043	Forecasting
Chong, Han & Park (2017)	38 stocks on KOSPI market, South Korea	three-layer deep neural networks	4th January 2010 to 30th December 2014	NMSE = 0.9638, RMSE = 0.8220, MAE = 0.5899 and MI = 0.0188	Forecasting
Krauss, Do & Huck (2017)	S&P 500, US	Ensemble techniques > DNN, GBT and Random Forest	December 1992 to October 2015	Mean Return per day = 0.0015, Maximum Drawdown = 0.4017, Calmar Ratio = 4.6277, RMSE = 0.0221	Classification, Trading
Kraus & Feuerriegel (2017)	CDAX Index, Germany	Traditional Machine Learning (Ridge regression, Lasso, Elastic Net, Random Forest, SVM, AdaBoost, Gradient Boosting) DL (RNN & LSTM) Transfer Learning (RNN & LSTM)	2010 to 2013	Direction (Accuracy = 0.579, Balanced accuracy = 0.583, AUC = 0.568) and Regression (RMSE = 6.029, MSE = 36.349 and MAE = 3.011)	Classification, Forecasting
Weng, Ahmed, & Megahed (2017)	Apple Stock on NASDAQ, US	Decision trees, neural networks and SVM	1st May 2012 to 1st June 2015.	Accuracy = 0.858, AUC = 0.838, F-measure = 0.879, G-mean = 0.873, MCC = 0.854, Precision = 0.719, Sensitivity = 0.858 and Specificity = 0.874	Classification
Chen & Hao (2017)	Shanghai Stock Exchange Composite Index and Shenzhen Stock Exchange Component Index, China	SVM and KNN	31st October 2008 to 31st December 2014	MAPE = 0.18 and RMSE = 0.0050	Forecasting
Gálvez & Gravano (2017)	8 stocks on MARVEL Index, Buenos Aires Stock Exchange market, Argentina	Ridge regression Random Forest	1st June 2010 to 31st July 2015	RMSE = 2.666 and Pearson's Product moment correlation coefficient = 0.472, accuracy = 0.733 and AUC = 0.751	Forecasting
Fischer & Kraus (2018)	S&P 500 index, US	LSTM, Random Forest, Logistic regression, FFNN	December 1989 to September 2015	Return = 0.46 %, Standard Deviation = 2.09 %, Sharpe Ratio = 5.83 and Accuracy = 54.3 %	Classification, Trading
Malagrino, Roman, & Monteiro (2018)	iBOVESPA index on São Paulo Stock Exchange, Brazil	Bayesian Networks	1st June 2005 to 5th April 2012	Accuracy = 77.78 %	Classification
Atkins, Niranjan, & Gerding (2018)	Indices of NASDAQ Composite and Dow Jones Industrial Average and equities of Goldman Sachs and J. P. Morgan, US	Latent Dirichlet Allocation (LDA) for topic modelling and naïve Bayes algorithm for classification	9 September 2011 to 7 September 2012	Random walk = 59.8, Recall = 53.3, Precision = 54.3, F1 = 52.9, MCC = 0.079	Classification
Kia, Haratizadeh, & Shouraki, (2018)	Gold spot price of 10Am London, prices of crude oil, indices of stock market of 36 stock exchanges in multiple countries	HYS3 Hybrid Supervised semi-supervised ConKruG + GSSL + SVM	17th September 2007 to 4th June 2015	Directional Accuracy = 74.26 % in OPEC	Classification
Zhu, Zhang, Liu, Wu, & Wang (2019).	Shanghai Futures Exchange (SHFE), China	Variational mode decomposition, Bidirectional gated recurrent unit, Hybrid model VMD-BiGRU	4th January 2006 to 15th July 2018	R Square = 0.997, RMSE = 0.004, MAPE = 0.021 and Directional Accuracy = 0.796	Forecasting
Basak, Kar, Saha, Khaidem, & Dey (2019)	Apple, Austria microsystems, Amazon, Facebook, Microsoft, Nike, Sony, TATA, Twitter, and TYO	Random Forest, Gradient boosted decision trees	Starting from the date of going public till 3rd February 2017	Accuracy = 78 %, Recall = 0.95, Precision = 0.93, Specificity = 0.90, F-Score = 0.94, Brier Score = 0.07 and AUC = 0.98	Classification and Trading
Sun, Xiao, Liu, Zhou, & Xiong (2019)	S&P 500, US	ARMA-GARCH-Neural Network	September 7, 2007 to October 15, 2007; June 11, 2008 to July 14, 2008: m June 17, 2009 to December 3, 2010	RMSE = 1.385 (U), 1.408 (D) and Accuracy 54.3 % (U), 52.6 % (D)	classification
Zhou, Zhang, Sornette, & Jiang (2019)	Shanghai Stock Exchange Composite Index China, Nasdaq Composite Index and S&P 500 Composite Stock Price Index US	LR2GBDT, Linear Regression, GBDT, SVM, Neural Network, TPOT	SSE:4th January 2010 to 31st December 2014: and US 3rd January 2012 to 23rd December 2016	Hit ratio = 0.68, Precission = 0.69, Recall = 0.79, F-measure = 0.73	Classification and trading
Lohrmann & Luukka (2019)	S&P 500 index, US	Random Forest	11th October 2010 to 28th March 2018	Accuracy = 44.78 %	Classification and trading
Long, Chen, He, Wu, & Ren (2020)	CITIC Securities, GF Securities and China Pingan, China	Deep Stock trend Prediction Neural Network = CNN + attention-based BiLSTM	March 2012 to June 2018	Accuracy = 0.7359, Balanced accuracy = 0.6191 and AUC = 0.7704	Classification
Li, Bu, Li, & Wu (2020)	CSI 300 index, China	LSTM, support vector machine (SVM), logistic regression, and Naïve Bayes model	1st January 2009, to 31st October 2014,	Accuracy = 80.20 %	Classification

(*continued on next page*)

Table 4 (*continued*)

Authors	Index/Stock, Country	Model	Time Period	Performance evaluation	Task
Maqsood, et al. (2020)	US (Apple, Citigroup, Google, Microsoft), Hong Kong (Bank of China, EverGreen, Ping Insurance Co, Tencent Holding ltd), Turkey (Arcelik, Dogus, Koc Holding, Vestel), Pakistan (Colgate, Toyota Motors, Unilever)	Linear Regression, SVM, Deep Learning	January 2000 to October 2018	RMSE = 0.043 +/- 0.009 and MAE = 0.025 +/- 0.003	Forecasting
Nevasalmi (2020)	S&P 500 index, US	K-NN classifier, Gradient Boosting, Random Forest, Neural Network, SVM	12th February 1990 to 5th October 2018	Classification accuracy = 0.5597	Forecasting And Trading
Kamdem, Essomba, & Berinyu (2020)	Crude oil, wheat, brent oil and silver, Cameroon and France	LSTM	01st January 2020 to 24th April 2020	Accuracy = 97.45 %	Forecasting
Liu & Long (2020) .	S&P 500 US, China Minsheng Bank Cina, Dow Jones Industrial Average US	Improved LSTM (EWT-dpLSTM-PSO-ORELM)	17 Dec 2010 to 17 Jan 2013, 18 Dec 2013 to 18 Jan 2016, 17 Dec 2014 to 17 Jan 2017	MAPE = 0.1071, MAE = 0.0215, RMSE = 0.0296, SDE (std dev of error) = 0.0252	Forecasting
Zhang, Chu, & Shen (2021)	103 stocks on SSE index, China	LSTM	January 2016 to March 2019	RMSE = 0.3721 and MAPE = 0.01356	
Ayala, Garcia-Torres, Noguera, Gomez-Vela, & Divina, (2021)	Indices of Ibex35 (IBEX) Spain, DAX Germany and Dow Jones Industrial (DJI) US	Multivariate Linear Regression, ANN, Random Forests, Support Vector Regression (SVR)	January 2011 to December 2019	RMSE = 625.06 ± 187.09, MAE = 466.21 ± 154.70, MAPE = 18.56 ± 6.12 and sMAPE = 18.61 ± 6.14	Trading
Keyan, Jianan, & Dayong (2021)	46 stocks of the SSE 50, China	RNN, LSTM and GRU	1st May 2017 to 28th July 2019	RMSE = 0.5698 and MAPE = 0.0235	Forecasting
Khattak, Ali, & Rizvi (2021)	EURO STOX 50 index, Europe	LASSO	1st January 2020 to 26th June 2020	**N/A**	Forecasting
Ingle & Deshmukh (2021)	Airtel, Bajaj, HDFC, Hero, ICICI, Idea, ITC, Maruti, Sun and TCS on BSE, India	GBM Regression GLM Deep Learning PCA + deep PCR + deep Km + deep	5th July 2016 to 9th August 2016	Minimum = 0.01 and maximum error rates = 13.31	Forecasting
Ye & Schuller (2021)	1,106 companies on Russell 1000 index, US	XGBoost	1997 to 2018	Classification accuracies = 60.86 %	Classification and trading
Kinyua, Mutigwe, Cushing, & Poggi (2021)	S&P 500 index (SPX) and the Dow Jones Industrial Average index (INDU)	Random Forest, Decision Tree and Logistic Regression	20th January 2017 and 18th October 2019	RMSE = 0.34, R sq. = 0.95	Classification and forecasting
Peng, Albuquerque, Kimura, & Saavedra (2021)	United States (S&P 100 Index), United Kingdom (FTSE 100 Index), France (CAC 40 Index), Germany (DAX-30 Index), Japan (Top 50 assets from NIKKEI 225 Index), China (Top 50 assetsfrom SSE 180 Index) and Brazil (Bovespa Index)	Logistic regression, ANN and deep neural network	01st January 2008 to 01st March 1st	Accuracy, precision, recall, and F-Score	Classification and forecasting
Zhang & Lou (2021)	Gree Electric, Maotai of Shanghai mainboard and BYD of small and medium-sized boards, China	BPNN	12th August to 12th Dec 2019	Accuracy = 73.29 %, MAE = 0.89 and MSE = 1.76	Forecasting
Eachempati, Srivastava, Kumar, Tan, & Gupta (2021)	Maruti Suzuki on NIFTY50, NSE, India	LSTM > RNN, SVM and Naïve Bayes	2011 to 2020	Accuracy = 72 %	Classification
Seong & Nam (2022)	SPX index, KOSPI index, US and South Korea	Attention based CNN + LSTM	1st January 1971 to 31st December 2019	Accuracy for short term = 0.602 Medium term = 0.660 and long term = 0.688 and Sharpe Ratio for short = 5.490 medium = 2.895 and long term = 3.239	Classification and Trading
Akhtar, Zamani, Khan, Shatat, & Dilshad, (2022)	BSE 500, DJIA, NASDAQ, India and US	Random Forest, SVM and LSTM	Extracted from Kaggle	Accuracy = 80.3 %	Forecasting
Gupta, Bhattacharjee, & Bishnu (2022)	CNX-Nifty, India	GRU based Stock-Net model	1st April 1996 to 6th January 2020	RSME = 0.0896 MAE = 69.9396 MAPE = 0.8203	Forecasting
Ma & Yan (2022)	CSI 300 index and Shanghai stock index, China	CNN	January 2007 to December 2021	Accuracy = 69.39 %	Forecasting
Park, Kim, & Kim (2022)	S&P500, SSE, and KOSPI200, US, China and South Korea	LSTM_Random Forest (Hybrid)	01st Aug 2002 to 13th September 2018	Regression: RMSE = 1.89, MAE = 1.41, and MAPE = 0.51 Classification: Accuracy = 59.83 Balanced accuracy = 59.95	Classification, forecasting and trading
Bhandari, et al. (2022)	S&P 500 index, US	LSTM	2006 to 2020	RMSE = 40.4574, MAPE = 0.7989 and R = 0.9976	Forecasting
Banik, Sharma, Mangla, Mohanty, & Shitharth (2022)	ICICI Bank and NIFTY-Bank from National Stock Exchange of India (Kaggle dataset)	LSTM	1st Jan 2020 to 31st July 2020	RMSE = 4.13 %, MAE = 3.24 %, and MAPE = 1.21 %	Forecasting
Pokhrel, et al. (2022)	Nepal Stock Exchange Limited (NEPSE)	LSTM, GRU, and CNN	17th July 2016 to 15th January 2020	RMSE = 10.4660 ± 0.6836, MAPE = 0.6488 ± 0.0502 and R = 0.9874 ± 0.0009	Forecasting

Source: Author's Compilation.

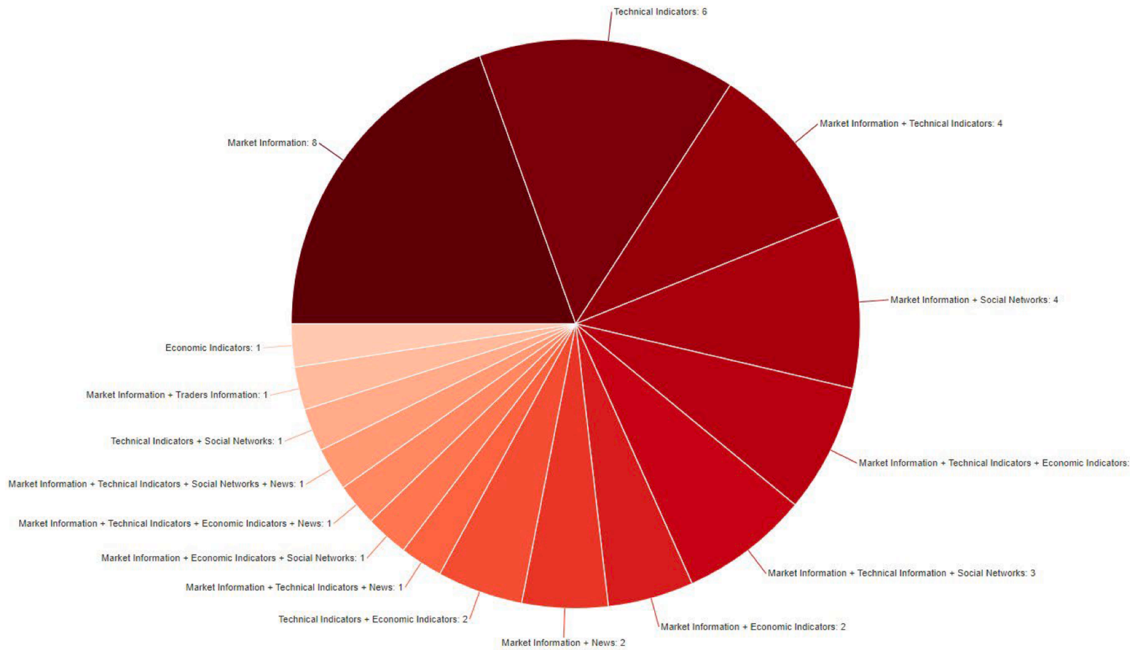

Fig. 1. Distribution of feature categories used for stock market prediction. **Source:** Author's Compilation.

Fig. 1). Long, Chen, He, Wu, & Ren (2020) use a fusion of stock market and trader's information to predict the next day's stock price direction.

The most frequently used technical indicators include: Moving Averages, Relative Strength Index (RSI), Williams R, and Stochastic K (Ayala, Garcia-Torres, Noguera, Gomez-Vela, & Divina, 2021). Studies adopted by Chen & Hao (2017) and Basak, Kar, Saha, Khaidem, & Dey (2019) use a combination of market information and technical indicators to predict the Shanghai Stock Exchange (SSE) Composite Index and Shenzhen Stock Exchange (SZSE) Component Index by the former and to predict the direction of prices of selected stocks by the latter.

Khattak, Ali, & Rizvi (2021) consider macroeconomic data such as gold prices, Oil prices, Bitcoin prices, EUR/USD exchange rate, and indices of stock markets across countries to find the predictors influencing the European market. Similarly, Kia, Haratizadeh, & Shouraki (2018) observe that a better market prediction model could be achieved by simultaneously using global market data of oil and gold prices along with historical indices of multiple countries to predict the target stock market and commodity prices' direction. Financial reports are also utilized to extract illiquidity, turnover, and Price/Earnings ratios (Zhang, Chu, & Shen, 2021; Keyan, Jianan, & Dayong, 2021).

Text mining is gaining popularity in the world of big data due to its ability to extract vast quantities of relevant information from news, blogs, speeches, and other social media websites that can enhance stock prediction. Similarly, market sentiment as an indicator is designed to represent the opinion of a group of people in a particular situation that is posted on social media platforms concerning a specific stock or the market in general. It basically involves discovering the polarity of statements, i.e., investors' positive, negative or neutral attitude towards the stock market, based on a news announcement on social media. For example, an analysis of the immediate 15 min impact of Trump's tweet on DJIA and the S&P500 index results in investors' negative reactions (Kinyua, Mutigwe, Cushing, & Poggi, 2021). Maqsood et al. (2020) analyse the impact of significant local and global event sentiments through a Twitter dataset on selected stocks from the US, Hongkong, Turkey, and Pakistan. Their findings illustrate that stock market volatility depends on community sentiments and the economic and political conditions of the country. Local events have an impact on the performance of prediction algorithms more significantly compared to global events. Saurabh & Dey (2020) discover the relationship between the social moods of people on the FTSE 100 index by employing ANN. They observe that the "happy" dimension could significantly improve the stock market's index return prediction. Heston & Sinha (2018) also find that positive news stories increase stock returns quickly, while negative stories receive a long-delayed reaction. An in-depth study on affective computing and sentiment analysis is undertaken by Erik Cambria (2016). Similarly, Weng, Ahmed, & Megahed (2017) harness stock-related Google news count and daily traffic on Wikipedia combined with technical indicators and historical data for intensifying stock prediction. Keyan, Jianan & Dayong (2021) propose another feature that extracted users' data and the stocks they followed on EastMoney to build an "investor-stock" network that trains deep learning models. All three models (LSTM, RNN, and GRU) achieve higher accuracy while combining the network variable with traditional variables rather than featuring traditional variables exclusively.

Zhang, Chu, & Shen (2021) draws attention to the inadequacy of relevant features by adding two novel investor attention proxies. These include media coverage, i.e., the number of daily news articles published about a particular stock and abnormal search volume on Baidu's index to the existing trading, liquidity, and traditional variables. When inputted into the LSTM model, these features favourably enhanced the stocks' closing price prediction accuracy listed on the SSE 50 index.

Accurately predicting the stock market calls for the selection of relevant features which serve as inputs to machine learning models. While some researchers do not explain the selection of input features to the model but continue to utilize features from previous studies, few researchers have used machine learning models to select the most effective and relevant features that influence the stock market. For example, Qiu, Song, & Akagi (2016) apply fuzzy curve analysis for the prediction of Japanese Stock Market; Baek, Mohanty, & Glambosky (2020) utilize Decision Tree, Genetic Algorithm, and Random Forest to study the influence of economic indicators on US stock market volatility; Lohrmann & Luukka (2019) apply Random Forest for feature selection for intraday prediction of stock return direction.

Researchers have attempted to predict the stock markets of emerging economies such as SSE 50 China, Ibovespa Brazil, and the KOSPI index in South Korea. Forecasting these stock markets is challenging as they are subject to high market volatility, growth, and investment potential. While most studies concentrate on forecasting the stock market for trading and investment purposes, a few studies utilize financial time series datasets to assess the robustness of the proposed model. The financial time series utilized for prediction include NASDAQ, S&P 500, and DJIA from the United States; SSE 50, CSI 300 and Shanghai Futures Exchange (SHFE) from China, Nikkei 225 index Japan, Ibovespa Brazil, Ibex35 Spain, and CDAX index and DAX index Germany. Some researchers use specific stocks such as Microsoft, Google, and Apple Inc (Das, Behera, Kumar, & Rath, 2018), Nepal Investment Bank (NIB), and Nabil Bank Limited (NABIL) (Saud & Shakya, 2020) for prediction. A study proposed by Hiransha, Gopalakrishnan, Vijay Krishna & Soman, 2018 trained the models by utilizing the day-wise closing price of TATA Motors listed on NSE to predict the closing prices of Chesapeake Energy (CHK) and Bank of America (BAC) listed on NYSE. This has been so due to the inner dynamics shared by both the stock exchanges in different countries.

4.1.2. Models for stock market prediction

Machine learning models have the edge over traditional prediction models, which do not consider the non-linearity in data. Classification models are used to obtain a binary output, i.e., to classify whether the stock would move upward or downward. In contrast, regression models forecast a particular value or trend of a stock/index. In addition, deep learning models are widely used in this area of study. While some studies focus on comparing models, a few have used ensemble models to enhance the accuracy of the output.

A study initiated by Atkins, Niranjan & Gerding (2018) used Latent Dirichlet Allocation for feature reduction and Naïve Bayes for text classification of financial news. Malagrino, Roman, & Monteiro (2018) also adopted the Bayesian Network to study the dependencies of stock market indices globally on the Ibovespa index. The author points out this model's simplicity and human-friendly visuals in understanding the conditional dependencies and frequency of co-occurrences. Correspondingly, Khattak, Ali & Rizvi (2021) also studies the influence of global market indices on the Eurostox50 index during the COVID-19 crisis using the Least Absolute Shrinkage and Selection Operator (LASSO) regression model. Selection and reporting of only essential variables and learning from the limited information available during a crisis are significant features of the model.

Basak, Kar, Saha, Khaidem & Dey (2019) adopted Random Forest and Gradient Boosted Decision Tree (GBDT) for a trading period ranging from 3 to 90 days for stock price direction classification. The study's findings indicate that the models are apt for trading over more considerable periods, as the accuracy increased with the increase in the trading period. Ayala, Garcia-Torres, Noguera, Gomez-Vela & Divina (2021) compared the performance of Random Forest and other models such as linear model, ANN, and Support Vector Regression (SVR) for developing trading signals. ANN models outperformed others, while the Linear model was most suitable for short-period prediction. An experimental framework proposed by Qiu, Song, & Akagi (2016) attempted to improve the accuracy of ANN, which was trained initially using the Back Propagation algorithm. Results prove that using a hybrid model that combines Genetic algorithm and Simulated Annealing outperforms Back Propagation in boosting the weights and bias used in ANN.

Chandra & Chand (2016) and Das et al. (2018) adopt a specific category of ANN, which includes RNN. Zhang, Chu & Shen (2021) point out the vanishing gradient and exploding gradient problem in the RNN model and apply the LSTM model, an advanced version of RNN that could overcome these drawbacks. (Saud & Shakya, 2020) compare the performance of LSTM to RNN and GRU on the datasets of Nepal and (Keyan, Jianan, & Dayong, 2021) on the datasets of the Shanghai stock exchange. According to the former results, GRU outperforms LSTM and RNN, while the latter favours LSTM over GRU and RNN. However, since these models were trained on different datasets and timeframes, it incapacitates us from weighing up any model. Li, Bu, Li, & Wu (2020) conclude through their study that utilizing investor sentiment as an indicator of the machine learning models proves the superiority of LSTM over logistic regression, Naïve Bayes and SVM. Further, a study proposed by M.A. Menon (2018) applied four deep learning models to predict the next 10-days' closing prices of certain stocks listed on NSE and NYSE. The study results indicate that CNN's capability of capturing abrupt changes in the data exceeds in performance compared to LSTM, MLP, and RNN. However, in contrast, the experimental results show that the LSTM model with 30 neurons provides a superior fit and high prediction accuracy, followed by GRU with 50 neurons and CNN with 30 neurons (Pokhrel, et al., 2022). A comprehensive study put forth by Kraus & Feuerriegel (2017) compares the performances of Naïve Baseline, traditional Machine Learning models: Ridge regression, LASSO, Elastic Net, Random Forest, SVM, AdaBoost, Gradient Boosting, Deep learning models: RNN & LSTM, and transfer learning: RNN and LSTM. Transfer learning using RNN and LSTM show significant results. Nabipour, Nayyyeri, Jabani, Shahab, & Mosavi (2020) compares machine learning models: Decision Tree, Random Forest, Adaptive Boosting, XGBoost, Support Vector Classifier (SVC), Naïve Bayes, KNN, Logistic Regression and ANN, and deep learning methods: RNN and LSTM. The results indicate that RNN and LSTM outperform all other prediction models on both; continuous and binary data. In recent years, the application of LSTM for stock market prediction is due to its better efficiency in learning how public mood impacts financial time series (Malandri, Xing, Orsenigo, Vercellis, & Cambria, 2018).

Sentiment analysis has proved crucial in predicting stock markets to determine whether the market is driven by rational decision-making or by investors' emotions and opinions. Xing, Cambria, & Zhang (2019) developed a Sentiment-Aware Volatility forecasting model, incorporating market sentiments for predicting fluctuations in stock markets. This novel model outperforms GARCH, EGARCH, TARCH, GJR-GARCH, Gaussian-process volatility model, and Variational neural models, including VRNN and LSTM. Ample studies focus on using market sentiments indicator to predict the future price of stock markets, while there is still considerable scope for predicting volatility driven by market sentiments.

In predicting the stock's direction, the average reported accuracy lies between 55 % and 65 % using various models such as random forest, Bayesian networks, and XGBoost. Weng, Ahmed, & Megahed (2017) conducted a comparison analysis wherein a situation combining market information, technical indicators, Google news counts, and generated features proved to have the highest accuracy of around 85 % using decision trees, SVM, and Neural networks. Li, Bu, Li, & Wu (2020) bring out the differences among models and provide evidence of the superiority of the LSTM model to SVM, Naïve Bayes, with an accuracy of 80.20 % when incorporating the hourly text-extracted investor sentiment indicator. In the case of forecasting, an LSTM model adopted by Kamdem, Essomba, & Berinyu (2020) , reported an accuracy of 97.45 %. The ability of the LSTM model to remember both long-term and short-term values has proved its superiority in treating financial time series, thereby becoming the preferred tool for time series analysis. In addition, they can handle very noisy data and work independently from the linearity assumption. Research shows that the models' accuracy can be further improved by incorporating transfer learning and word embedding.

4.2. Portfolio management

Portfolio management includes several tasks such as selecting assets to form the portfolio, prioritizing assets based on risk tolerance and returns expected, and formulating suitable portfolio strategies. It also includes revising these strategies and rebalancing portfolio composition from time to time to achieve long-term or short-term financial goals. Due to these many related tasks, portfolio selection, portfolio allocation, and portfolio optimization have been used interchangeably in previous literature but with the same underlining aspect of managing a portfolio (Ozbayoglu, Gudelek, & Sezer, 2020). Portfolios are constructed in a way such that the assets contained in them can outperform the market's cross-sectional median or benchmark index. Markowitz (1952) designed the Mean-Variance (MV) portfolio, wherein the average of the historical data of a stock's return is the expected return, and the variance of these returns acts as the risk (Milhomem & Dantas, 2020). Majority of the studies to date utilize the MV portfolio strategy. Paiva, Cardoso, Hanaoka & Duarte (2019), Chen, Zhang, Mehlawat & Jia (2021), and Wang, Li, Zhang & Liu (2020) combine machine learning techniques to MV portfolio strategy. These results exceed the 1/N portfolio strategy wherein an equal share was invested across the "N" assets available. Ma, Han, & Wang (2021) analyse two portfolio selection techniques: MV and Omega portfolio, using machine learning and deep learning models. Vo, He, Liu & Xu (2019) propose a reinforcement learning model incorporating MV and Environmental Social Governance ratings (MV-ESG) to create a socially responsible investment portfolio.

Another aspect concerns transaction costs incurred in the real world while purchasing or selling assets. Few authors have implemented portfolio management strategies without considering transaction costs, while others have accounted for the same. Some have also established a comparative study on both these situations, which are reflected in Table 5. Recent activity in portfolio management includes online portfolio selection, wherein decisions are taken through an online manner as and when financial data is updated. Reinforcement learning is gaining popularity in investment portfolios due to its ability to make decisions by observing the state of the environment. This section reviews the scanty search results associated with machine learning and portfolio management and its closely related functions such as asset selection, portfolio allocation, portfolio construction/formation, and portfolio optimization.

4.2.1. Features and datasets for portfolio management

High-quality stocks are selected based on their predicted return to form a portfolio. These returns are predicted using fundamental as well as technical indicators. Koratamaddi, Wadhwani, Gupta & Sanjeevi (2021) incorporated market sentiments from Google News and Twitter tweets. Concerning the input features used for reinforcement learning models, Vo, He, Liu & Xu (2019) utilized the prediction error to depict whether the market was bullish or bearish. Most studies use only fundamental data: historical open, high, low, close price, and volume traded data to form their portfolios. Some models are also trained using a combination of fundamental and technical indicators (see Fig. 2). While technical analysis is based on mathematical indicators constructed from stock prices, fundamental analysis exploits information retrieved from news, profitability, and macroeconomic factors. Picasso, Merello, Ma, Oneto, & Cambria (2019) used technical analysis and exploited news articles' sentiments as input to forecast the trend of twenty companies on the NASDAQ100 index of a portfolio. They achieved more than 80 % of annualized returns by implementing a trading simulation. The study represents a step forward in combining technical and fundamental analysis and developing new trading strategies. Xing, Cambria, & Welsch (2018) proposed a sophisticated approach to compute the asset-level market sentiment from social media data stream, and integrate it to asset allocation method using market views.

Almost all portfolios were formed using daily historical stock prices, covering stocks from CSI 100, CSI 300, CSI 500, HIS, SSE 50, Nifty50, Ibovespa, S&P 500, DJIA, NYSE, AMEX, NASDAQ, and FTSE 100. Barua & Sharma (2022) form portfolios using historical data from ten sectoral indices of MSCI Asia Pacific, extracted from the Bloomberg database. (Betancourt & Chen, 2021) tested the cryptocurrency dataset involving 30 min, 6 h, and daily prices of Bitcoin, Ethereum, Litecoin, and 82 others from Binance. However, Vo, He, Liu & Xu (2019) retrained the models after each testing period, i.e., quarterly and yearly.

It is difficult for investors to hold too many stocks and measure their performance regularly. Hence, Paiva, Cardoso, Hanaoka & Duarte (2019) recommend that an average of 7 assets in a portfolio be held per day. Based on this precept, Chen, Zhang, Mehlawat & Jia (2021) created a portfolio consisting of stocks with a cardinality ranging from 6 to 10, while Wang, Li, Zhang, & Liu (2020) used 4 to 10 stocks. It is apparent from Table 5 that majority of the studies consider using ten or fewer stocks as an individual investor can easily manage them. However, Tan, Yan & Zhu (2019) selected 20 stocks to form the portfolio to be held for 20 days, and Vo, He, Liu & Xu (2019) empirically tested that the ESG portfolio best performed when it consisted of 7, 18 and 12 particular stocks in 2016, 2017 and 2018 respectively.

4.2.2. Models for portfolio management

Paiva, Cardoso, Hanaoka, & Duarte (2019) use SVM as a binary classifier for day trading operations intending to gain a specific target daily return of 1 %, 1.5 %, and 2 %. The proposed model SVM + MV outperforms SVM + 1/N and Random + 1/N. Based on cumulative returns, this model outperforms the alternative models in both scenarios: with and without transaction cost. Chen, Zhang, Mehlawat & Jia (2021) employ XGBoost with an improved firefly algorithm for stock price prediction combining it with the MV model to construct a portfolio. Tan, Yan, & Zhu (2019) use Random Forest to select stocks from the Chinese stock market in the short and long run.

According to a comparative study undertaken by Wang, Li, Zhang & Liu (2020), LSTM + MV outperformed LSTM + 1/N, SVM + MV, and SVM + 1/N in portfolio optimization by achieving higher annual cumulative returns, Sharpe ratio per triennium, and average returns to risk. Contradictory to the performance of the LSTM + MV model, another comparative study indicates the superior performance of Random Forest + MV in portfolio optimization (Ma et al., 2021). The author compared machine learning models: Random Forest, SVR; deep learning models: CNN, Deep MLP, and LSTM; and Linear model: Autoregressive Integrated Moving Average (ARIMA) incorporated with MV and Omega Portfolio forecasting. The study uses non-technical indicators to run these models.

Previous studies adopt a two-step approach: forecasting future returns and taking appropriate trading decision rules. However, Koratamaddi et al. (2021) apply deep reinforcement learning techniques to create an intelligent automated trader that would merge the two steps and act as an investor in the real world. The model adopted was called Adaptive Sentiment-Aware Deep Deterministic Policy Gradients (DDPG). By providing an initial investment of U.S.$ 10,000, the trader agent was allowed to trade up to 5 stocks at once, taking only one action decision a day. The portfolio value was much higher on using Adaptive Sentiment-Aware DDPG than other approaches such as DDPG, Adaptive DDPG, and traditional MV and Minimum Variance daily. Thus, the use of Reinforcement learning in portfolio management has witnessed an elimination of tedious activities that an investor would otherwise have to perform. Table 5 displays the models used and their over/underperformance.

Sharpe ratio is the most commonly used metric to weigh investments. It represents an amount of return (in units) obtained by taking a unit of risk. The greater a portfolio's Sharpe ratio, the better its risk-adjusted performance. Amongst all the models under review, Juan (2022) reports the highest Sharpe Ratio of 9.31, using an Attention-based LSTM network to form a portfolio with 20 stocks from CSI 300. Although the same model is used to form a portfolio with stocks from S&P500, the reported Sharpe Ratio is 2.77. This model, combined with statistical arbitrage, can generate positive trading performance based on the daily and weekly returns of S&P 500 stocks. We find that that stock selection technique based on probability ranking results in a higher portfolio net value than a hedged portfolio. The remaining models report Sharpe ratios below 3 (see Table 5). In the real world, investors are concerned with the returns they achieve through trading strategies and do not wholly rely on the Sharpe ratio. The returns were reported daily, monthly, or annually. The trading agent reported the highest daily return based on deep reinforcement learning at over 24 %. In a comparative study, Random Forest outperforms SVR, LSTM, CNN, MLP, and ARIMA with excess returns of 121.53 % coupled with the Omega Portfolio strategy. On an annual basis, we found that, while most studies

Table 5
Financial application of machine learning in portfolio management.

Title	Index/stocks	Models	Portfolio strategy	Time period	Transaction cost	Number of stocks in portfolio	Performance evaluation
Tan, Yan & Zhu (2019)	20 Stocks from Chinese Stock market and benchmark: CSI 500	Random Forest and DNN > Linear Regression	Selected stocks compared to benchmark index	8/2/2013 to 8/8/2017	Transaction cost @ 0.16 %	20 stocks	Annual returns = 185.56 %, MDD = 0.569, Sharpe ratio = 5 and Calmar ratio = 2.4618
Paiva, Cardoso, Hanaoka & Duarte (2019)	53 to 73 stocks listed on Ibovespa index, São Paulo Stock Exchange	SVM	Mean-Variance Portfolio compared to 1/N	June 2001 to December 2016	With and Without transaction cost @1.00, 0.50, 0.10, and 0.05 bps	7 stocks	Precision = 54.97 %, Specificity = 70.29 %
Vo, He, Liu & Xu, (2019)	100 stocks on S&P 500 index	bilSTM for forecasting returns and Reinforcement learning for retraining the model every quarter or year	Mean- Variance with Environmental Social Governance (ESG)	31/12/1988 to 31/12/ 2018	Without transaction cost	7,18 and 12 stocks in 2016, 2017 and 2018	Annual returns = 26.60 %, Volatility = 14.31 %, Sharpe Ratio = 1.7191 and ESG Score = 71
Wang, Li, Zhang & Liu (2020)	21 stocks from FTSE 100, UK	LSTM > SVM, Random Forest and ARIMA	Mean-Variance Portfolio compared to 1/N	March 1994 to March 2019	With and Without transaction cost @ 0.05bps and 0.1 bps	4 to 10 stocks	Mean Return = 0.1367, Standard Deviation = 0.2125, Sortino ratio = 13.7078 and Sharpe Ratio = 0.3218
Ma et al. (2021)	49 stocks from China securities 100 index	Random Forest > SVR, LSTM, CNN, DMLP and ARIMA	Mean-Variance and Omega Portfolio	4/1/2007 to 31/12/2015	With and Without transaction cost @0.05 %	N/A	Excess return = 121.53 %, standard deviation = 1.3980, information ratio = 0.8693, total return = 679.36 %, maximum drawdown = 70.42 % and turnover rate = 149.72 %
Chen, Zhang, Mehlawat & Jia (2021)	24 stocks on Shanghai Stock Exchange (SSE) 50 index	XGBoost with improved firefly algorithm (IFA)	Mean-Variance Portfolio compared to 1/N	November 2009 to November 2019	With transaction cost @ 0.5 % and 1 %	6 to 10 stocks	Annual mean return = 0.1177, annual standard deviation = 0.1879, annual Sharpe ratio = 0.4667, and annual Sortino ratio = 0.6580
Koratamaddi et al. (2021)	30 companies on Dow Jones Industrial Average index	Adaptive Deep Deterministic Policy Gradients (DDPG) compared to Mean Variance, Minimum Variance, DDPG, Adaptive DDPG and Adaptive Sentiment Aware DDPG	Agent trader Compared to Mean-Variance, Minimum Variance	1/1/2001 to 2/10/2018	Without transaction cost	trade 5 stocks per day maximum	Sharpe Ratio = 2.07, Annual returns % = 22.05, and annual std error = 0.096
Kwak, Song, & Lee (2021)	487 stocks on S&P 500 index and Hang Seng Index (HSI)	Neural Network	Equally-weighted portfolio (1/N)	01st July 2014 to 31st December 2019	Without transaction cost	Number of stocks in the portfolio include: 50, 100, 200 and 487	RMSE = 0.0239, average daily return = 0.9427, volatility of the daily return = 0.0032
Betancourt & Chen (2021)	Bitcoin, Ethereum, Litecoin and others. the number of active assets that can be exchanged for USDT incremented from three to 85	Deep Reinforcement Learning	Agent trader	17th August 2017 to 01st November 2019	With transaction fees (except BNB) 0.1 % and fees BNB 0.05 %	Dynamic number of assets	Average daily returns of over 24 %, Sharpe ratio = 0.46
Mohiuddin (2021)	50 stocks on Nifty50, NSE	LSTM > MLP	Predictive Performance Model compared to Markowitz Mean-variance model and Mean Semi-variance model	01st January 2018 to 23rd April 2021	Without transaction cost	Number of stocks in each portfolio vary from 1 to 50	RMSE for stock prediction and expected returns were set between 0.0210 and 0.0270. Weights were determined according to the returns to be achieved
Alexandre (2022)	572 Brazilian stocks, Ibovespa index	Linear regression with and without regularization (via LASSO and ridge), Bayesian variable selection, Random	Equal Risk Contribution is better than long short strategies	January 2003 to December 2018	With transaction cost @ 0.15 % for all trades, i.e., a bid-ask spread of 0.30 %	Number of stocks in each portfolio vary from 10 to 40	Average monthly return before cost = 2.06 and after costs = 1.23, the monthly standard deviation = 2.94, the annual

(continued on next page)

Table 5 (*continued*)

Title	Index/stocks	Models	Portfolio strategy	Time period	Transaction cost	Number of stocks in portfolio	Performance evaluation
		Forests, gradient boosting, and neural networks and Ensemble model					Sharpe Ratio before cost = 2.10 and after costs = 1.13, the maximum drawdown = 19.27, average monthly turnover = 117.12, and average leverage = 1.66
Juan (2022)	20 stocks from CSI 300 and 20 stocks from the S&P 500	SVM, Random Forest, and Attention-based LSTM	Mean-Variance Portfolio compared to 1/N	May 4, 2012 to August 4, 2020.	Without transaction cost	Less than 20 stocks	Accuracy = 92.59 % (CSI 300) and 88.52 % (S&P 500), Sharpe ratio of 9.31 (CSI 300) and 2.77 (S&P 500)
Pinelis and Ruppert (2022)	NYSE, AMEX, and NASDAQ indices	Random Forest, Elastic Net and Linear model	Buy and Hold market strategy	1927–2019	With an increase in transaction cost @ 1bps, 10bps and 14bps for trading approximately 1 % of daily volume	N/A	Sharpe Ratio = 0.68, Annualized returns = 12 %-13 % and standard deviation = 13 to 15 %
Barua & Sharma (2022)	MSCI Asia Pacific sector indices: Energy, Utilities Consumer, Health Care, Communication Services, Information Technology, Consumer Staples, Discretionary, Materials, Financials & Industrials	Hybrid: CNN-BiLSTM	Buy and Hold market strategy	01st April 2002 to 31st March 2022	With transaction costs @ 25 basis points	N/A	Sharpe Ratio = 2.55 and Herfindahl Index = 0.128

Source: *Author's Compilation.*

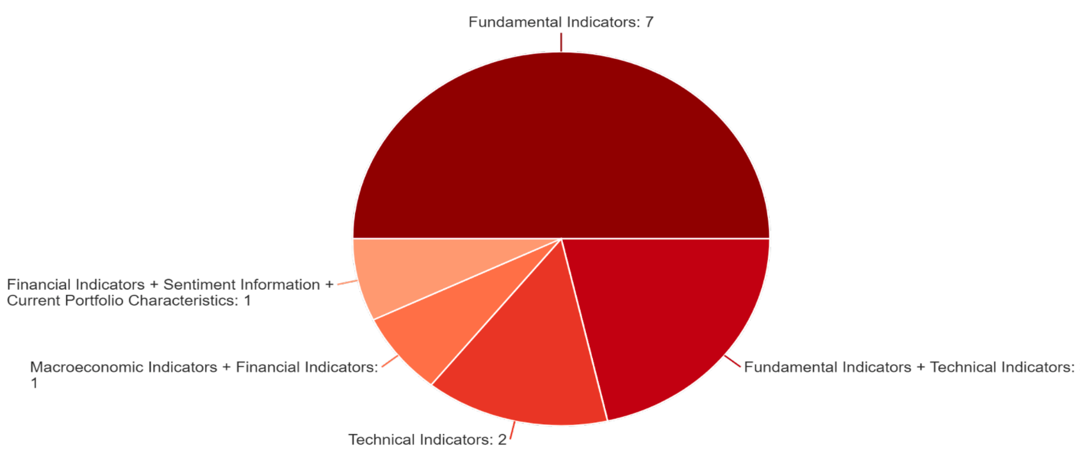

Fig. 2. Distribution of feature categories used for portfolio management. **Source:** Author's Compilation.

report returns ranging between 10 % and 30 %, the portfolio's annualized return reaches 185.56 % during the oscillating market period. This indicates that significant excess returns with diminished volatility are exploitable in the short forward period. The study compares the performance of two different datasets belonging to CSI 300 and S&P500. We find that a higher accuracy was obtained on the CSI at 92.59 % compared to 88.52 % on S&P 500. Interestingly, the highest returns in both situations were achieved by applying Random Forest model to China Securities Index datasets.

4.3. *Cryptocurrency prediction*

Cryptocurrency allows people to transact by avoiding the involvement of third parties. Unlike traditional currencies, cryptocurrencies are a network-based medium that facilitates digital exchange using strong cryptographic algorithms to secure records (Patel, Tanwar, Gupta, & Kumar, 2020). It is believed that Satoshi Nakamoto came up with the initial notion of Cryptocurrency back in 2008 when he realised the need for a peer-to-peer electronic cash system. This meant no involvement of Government, financial institutions, or any other third parties, and the transactions would be tracked through blockchains, ensuring transparency (Nakamoto, 2008). This, in turn, meant that the currencies were not governed, regulated, or validated by third parties, making them highly volatile. It is difficult to assess the risk of such a currency based on public perception and can lead to devaluation overnight (Chowdhury, Rahman, Rahman, & Mahdy, 2020). However, many attempts are made to predict future cryptocurrency prices and volatility. This section reviews the literature on predicting prices of specific cryptocurrencies like Bitcoin, Ethereum, Litecoin, Monero, Dogecoin, and many more Table 6.

4.3.1. *Features and datasets for cryptocurrency prediction*

Similar to stock market prediction, cryptocurrency prediction relies on historical data: Open, high, low, and close prices along with volume. A study on intraday price prediction uses a small feature space comprising only five lagged prices to predict the next 5-min price (Lahmiri & Bekiros, 2020). The study concludes that these five inputs could effectively predict bitcoin prices and including additional inputs would not be advantageous. Cryptocurrency data such as block size, hash rate, mempool transaction count, mempool size, and more are combined with Google Trend Search Volume Index and the gold spot price for price prediction (Chen, Li, & Sun, 2020). Similarly, Mallqui & Fernandes (2019) use macroeconomic indicators such as crude oil futures prices, gold futures prices combined with S&P500 futures, NASDAQ futures, and DAX index historical price data to predict the direction, maximum, and minimum closing bitcoin prices. The authors suggest the use of technical indicators to improve prediction accuracy. This was proven in the works of Alonso-Monsalve, Suárez-Cetrulo, Cervantes & Quintana (2020), wherein technical indicators such as RSI, MACD, CCI, and momentum are used as inputs for predicting intraday trend classification. Thus, the indicators used for cryptocurrency prediction vary across the historical prices, technical indicators, economic indicators, and news search engines, in addition to cryptocurrency market data. Out of the 19 articles reviewed in this area, 9 of them make use of only historical information (see Fig. 3).

For intraday trade prediction, hourly or minute data was used (high frequency), while daily datasets were used for predicting the day's closing prices (low frequency). A frequency study concludes that errors, RMSE, and MAE obtained from low-frequency data were higher than in high-frequency data (Peng, Albuquerque, Camboim de Sa, Padula, & Montenegro, 2018). The datasets were mainly obtained from cryptocurrency websites such as https://coinmarketcap.com, https://bitcoincharts.com, https://coindesk.com, and financial databases.

4.3.2. Models for cryptocurrency prediction

Throughout the discussions across different financial applications, machine learning models have performed better than statistical models. Nevertheless, a study comparing these models indicate that statistical models such as linear regression and LDA outperform machine learning models in predicting daily bitcoin prices. Meanwhile, machine learning models outperform statistical models in 5-min bitcoin price prediction (Chen, Li, & Sun, 2020). This indicates the superior performance of machine learning models in high-frequency data. M et al. (2020) compare the performance of linear regression algorithm and SVM with radial basis kernel to predict the price of ether. While linear regression does not provide satisfactory results, SVM's was significantly better. Moreover, using feature engineering to select relevant features, the accuracy obtained by the SVM algorithm was even higher than the previous results. In line with this, Liu, Li, Li, Zhu, & Yao (2021) empirically tested SVR, BPNN, and Stacked Denoising Autoencoders (SDAE). The evaluation metrics indicate that SDAE has the highest predictive ability for forecasting directional and level prediction of bitcoin price. In another study, SVM, ANN with single and double hidden layers, and ensemble models (based on RNN and k-Means clustering) predict the maximum, minimum, and closing bitcoin prices. While these models performed effectively well, using the regression outputs as inputs to predict the direction of bitcoin prices increased the accuracy by 10 % (Mallqui & Fernandes, 2019). Attempts to analyse the performance of LSTM, Stacked LSTM, BiLSTM, and GRU; show that LSTM and GRU models are highly recommendable in real-time Ethereum price prediction (Zoumpekas et al., 2020). The LSTM model outperforms the hybrid LSTM + GRU model in predicting Litecoin and Monero prices (Patel, Tanwar, Gupta, & Kumar, 2020).

In the case of cryptocurrency price prediction, the SVM model with feature extraction gains an accuracy of 99 % in predicting the price of Ethereum (Poongodi, et al., 2020) and LSTM at 67.20 % for predicting the Bitcoin price (Mallqui & Fernandes, 2019). For daily direction prediction, Ortu, Uras, Conversano, Bartolucci, & Destefanis (2022) reports an accuracy of 99 % for Ethereum, while 57 % accuracy is achieved in the case of Bitcoin. Here an LSTM model is trained using technical indicators alone. The accuracy of adding social network information drops to 87 % for Ethereum and 46 % for Bitcoin. However, on adding trading indicators to the existing indicators, accuracy for Ethereum increases by 2 %, while that of Bitcoin decreases by 2 %. Further research in this area could highlight whether trading indicators cause an improvement or not in predicting the other cryptocurrencies. Overall, out of the top 25 ranking cryptocurrencies, we find ample articles predicting Bitcoin and Ethereum prices, (which rank at the first and second position respectively as on 15th August 2022), followed by Litecoin, but not as much on the other cryptocurrencies (see Fig. 4). Existing articles predicting other cryptocurrency prices such as Monero, Ripple, and Santiment have relatively lower accuracy. This highlights the need to find appropriate machine learning models that can predict the future prices of other cryptocurrencies, thereby helping investors develop profitable trading strategies.

4.4. Foreign exchange markets

Globally, the Foreign Exchange (Forex) market ranks as the largest financial market, where trading takes place in the form of currency pairs (Moghaddam & Momtazi, 2021; Islam & Hossain, 2020). Forex rates are determined based on supply and demand and trades take place based on the bid-ask price. The high volatility of this market complicates the prediction of future prices of currency pairs (Ahmed, Hassan, Aljohani, & Nawaz, 2020). Various fundamental and technical analyses are undertaken in this regard.

There is a widespread use of machine learning techniques in the Forex Market. This literature covers its application in the foreign exchange rate and direction prediction, development of forex trading strategies, determination of profitable forex trading signals, risk management in forex trades, and prediction of foreign exchange reserves of a nation. EUR/USD pair is identified to be the most traded currency pair (Moghaddam & Momtazi, 2021). The literature under review has witnessed the prediction of EUR/USD as the most common, considering it to be the most prominent standard for exchange rates, followed by USD/GBP (see Fig. 5). This indicates that most studies have attempted to predict forex rates between North America and Europe.

4.4.1. Features and datasets for forex prediction

For predicting the forex rates of currency pairs, the wonted feature inputs were the open, high, low, and close price of the forex rate understudy. Islam & Hossain (2020) and Gerlein, McGinnity, Belatreche & Coleman (2016) incorporate technical inputs along with these essential features, while Shen, Chao & Zhao (2015) use the past lagged observations of exchange rates. Semiromi, Lessmann & Peters (2020) use historical data, technical indicators, and retrieved economic news events data to predict intraday forex directional movement. Ahmed, Hassan, Aljohani & Nawaz (2020) utilizes candles as inputs to predict the next 4 h (H4) candle. Extending this, Moghaddam & Momtazi (2021) use candlestick image data as inputs to predict the profitability or non-profitability of trading signals in the forex market. A risk management tool was developed considering 20 feature inputs, out of which 14 were technical indicators corresponding to the prices of the Modified Renko Bars (MRB) chart (Chandrinos, Sakkas, & Lagaros, 2018). Table 7 presents the various features used in each study.

The datasets consist of per minute, hourly, daily, and weekly time frames of the respective exchange rates for prediction. Ahmed, Hassan, Aljohani & Nawaz (2020) utilize H4 candle data to predict the next 4 h candle for EUR/USD. Chanda, Bandyopadhyay, & Banerjee (2020). utilize various annual reports, five-year plan documents, economic surveys, and expenditure budgets from the Department of Commerce and Ministry of Commerce and Industry to forecast the foreign exchange reserves of India.

4.4.2. Models for forex prediction

According to Gerlein, McGinnity, Belatreche & Coleman (2016), simple and traditional machine learning models can be employed to

Table 6
Financial application of machine learning in cryptocurrency prediction.

Title	Dataset/Source	Model	Period	Performance Metrices	Task
Mallqui & Fernandes (2019)	Daily historical data OHLC and external datasets on economic indicators, https://bitcoincharts.com, https://quandl.com, https://investing.com	ANN, SVM < Ensemble algorithms (based on Recurrent Neural Networks and the k-Means clustering method)	April 1st, 2013 to April 1st, 2017	Accuracy = 62.91, MAPE = between 1.28 % and 1.91 %, MAE = between 6.70 and 9.63	Predicting direction, maximum, minimum, closing daily price of bitcoin
Chen, Li, & Sun (2020)	Daily price from https://www.coinmarketcap.com	LSTM > Linear Regression, LDA, QDA, Random Forest, XGBoost, SVM	February 2, 2017, to February 1, 2019	Accuracy = 0.672, precision = 0.722, recall = 0.840 and F1 score = 0.776	Predicting bitcoin price
M, et al. (2020)	https://etherchain.org/programminginterface/measurements/cost,	SVM > Linear Regression	N/A	Accuracy = 99 %	Predicting Ethereum price
Chowdhury, Rahman, Rahman, & Mahdy (2020)	Seven-day week daily data from https://www.coinmarketcap.com	Gradient boosted trees, Neural net, Ensemble learning, K-NN	Testing for 1st January 2019 to 31st January 2019	RMSE = 0.002 and Accuracy = 92.4 %	Predicting closing prices of Bitcoin Cash; Bitcoin; Dash; Doge coin (DOGE); Ethereum; IOTA (MIOTA); Litecoin; NEM; NEO
Zoumpekas, Houstis, & Vavalis (2020)	Historical data from Poloniex exchange	LSTM network, the Stacked LSTM network, the Bidirectional LSTM network, and the Gated Recurrent Unit network.	August 8, 2015 to May 28, 2018	RMSE = 0.92 +/- 0.26 and MAE = 0.50 +/- 0.19	Predicting closing price of ETH/USD
Patel, Tanwar, Gupta, & Kumar (2020)		LSTM < Hybrid GRU + LSTM	Litecoin: August 24, 2016 - February 23, 2020 and Monero: January 30, 2015 - February 23, 2020	MSE = 4.1319, RMSE = 2.0327, MAE = 1.5425, and MAPE = 2.0581	Price prediction of Litecoin and Monero
Alonso-Monsalve, Suárez-Cetrulo, Cervantes, & Quintana (2020)	Cryptocompare	Hybrid CNN-LSTM > CNN, RBNN, MLP	1st of July of 2018 to the 30rd of June of 2019,	Average excess prediction accuracy: Mean = 5.354 % and Best = 11.064 %	Prediction of intraday trend classification of cryptocurrencies
Lahmiri & Bekiros (2020)	N/A	SVR and Gaussian Poisson regressions, regression trees, kNN, FFNN, Bayesian regularization and radial basis function networks (RBFNN)	1 January 2016 to 16 March 2018.	RMSE = 0.8443	Predicting Intraday bitcoin price
Liu, Li, Li, Zhu, & Yao (2021)	https://www.coindesk.com and BTC.com, Baidu and google, Wind financial database and the Choice financial database, Thomson Datastream database	SDAE > BPNN and SVR	July 2013 to December 2019	RMSE = 160.63, MAPE = 0.1019 and DA = 0.5985	Predicting bitcoin price
Ibrahim, Kashef, & Corriga (2021)	5-min OHLC data for Apple, Facebook, Google, and Microsoft stocks from Google Finance API and https://www.coinbase.com/	MLP > ARIMA, Prophet (by Facebook), Random Forest, Random Forest Lagged-Auto-Regression	2014 onwards	Accuracy = 54.9 %	Predicting bitcoin price movement (classification)
Kim, Bock, & Lee (2021)	Daily Ethereum prices from Etherscan	ANN(MLP) > SVM	August 11, 2015 to November 28, 2018	RMSE = 0.068 and MAPE = 0.048	Predicting Ethereum price
Jaquart, Dann, & Weinhardt (2021)	Minutely data from Bloomberg, Twitter and Blockchain.com	GRU, LSTM, FNN, Logistic regression, Gradient Boosting Classifiers and Random Forest	March 4, 2019 to December 10, 2019	Predictive accuracy = 0.55	Predict bitcoin price at 1 min, 5 min, 15 min and 60 min ahead
Nasirtafreshi (2022)	https://www.coinmarketcap.com	RNN > ARIMA SVR, Random Forest -Regressor, XGB-Regressor, MLP, LSTM, GRU, CNN, LSTM + CNN, GRU + CNN	15 September 2016 to 5 November 2018	RMSE = 7.48e + 00 MAE = 5.93e + 01 MAPE = 3.21e + 00 R-squared = 9.43e − 01	Predicting daily close price and fluctuations
Ortu, Uras, Conversano, Bartolucci, & Destefanis (2022)	Bitfinex exchange service	MLP, CNN, LSTM, neural network and Attention based-LSTM	January 2017 to January 2021	accuracy = 0.99, f1_score = 0.99, precision = 0.99 and recall = 0.99	Predict the hourly and daily classification of Ethereum and Bitcoin price movements
Basher & Sadorsky (2022)	Daily bitcoin prices from Yahoo Finance	Random Forest	17th September 2014 to 29th December 2021	Annualized mean = 120.79 %, standard deviation = 44.19 %, and Sharpe Ratio = 2.73	Predicting Bitcoin price direction
D'Amato, V., Levantesi, ***&*** ***Piscopo*** (2022)	https://www.coinmarketcap.com	Jordan Neural Network	Upto December 16th, 2019	MSE = 0.000527 and MAPE = 0.641597	Predict the volatility of cryptocurrencies
Rathore, et al (2022)	https://www.kaggle.com/team-ai/bitcoin-price-prediction/version/1	Fb_prophet, LSTM and ARIMA	28th April 2013 to 31st July 2017	Graph	Predict closing price of Bitcoin
Wang, Shen, & Li (2022)	Google trends and twitter sentiments from BitnfoCharts and	LSTM	January 1, 2016 to May 1, 2020,	RMSE = 394.058 and MAPE = 0.035	Predict Bitcoin returns

(*continued on next page*)

Table 6 (*continued*)

Title	Dataset/Source	Model	Period	Performance Metrices	Task
Wang, Wang, Sensoy, Yao, & Cheng (2022)	Bitcoin prices from https://www.coinmarketcap.com Bitfinex exchange transactions obtained from Kaiko Database	Random forest, logistic regression, SVM, LSTM and ANN	August 13, 2017 to March 9, 2021	Accuracy = 65.04 %	Predict cryptocurrency direction

Source: Author's Compilation.

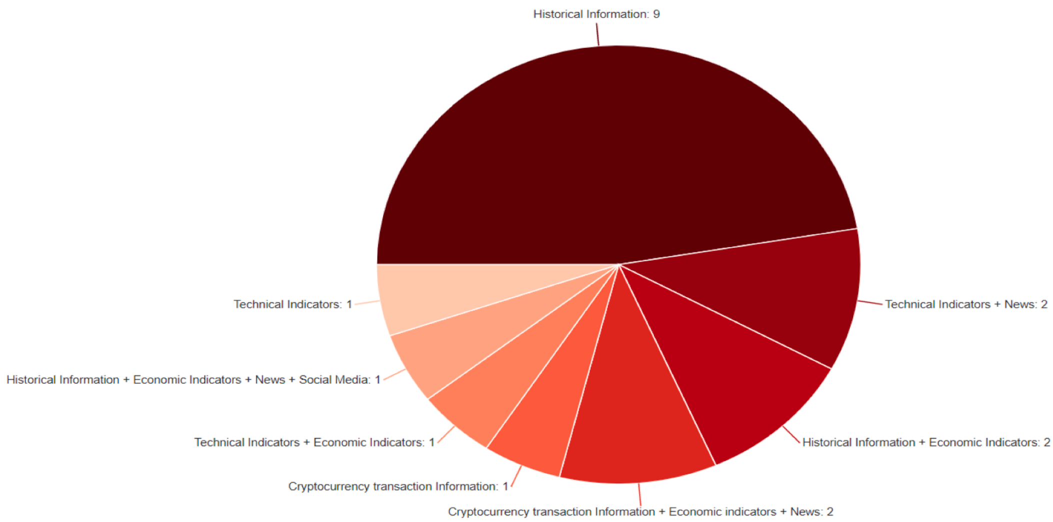

Fig. 3. Distribution of feature categories used for cryptocurrency prediction. **Source:** Author's Compilation.

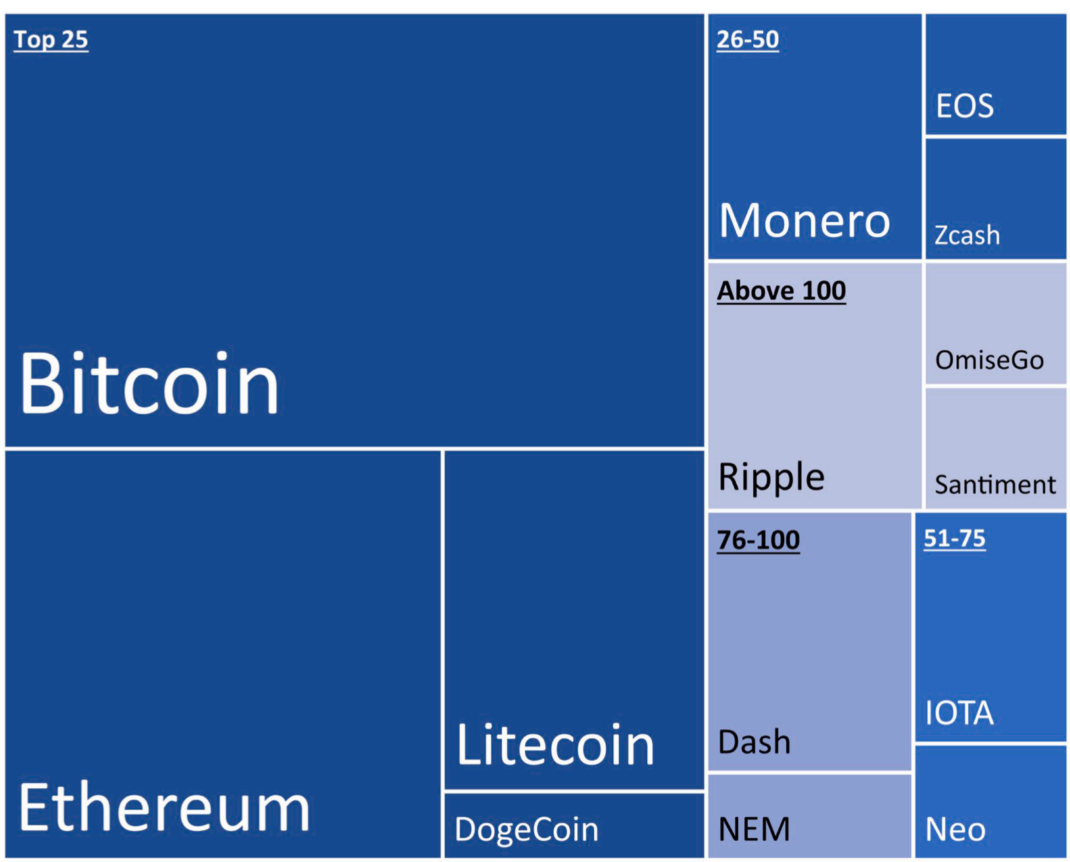

Fig. 4. Prediction of Cryptocurrencies in different ranking categories **Source:** Author's Compilation.

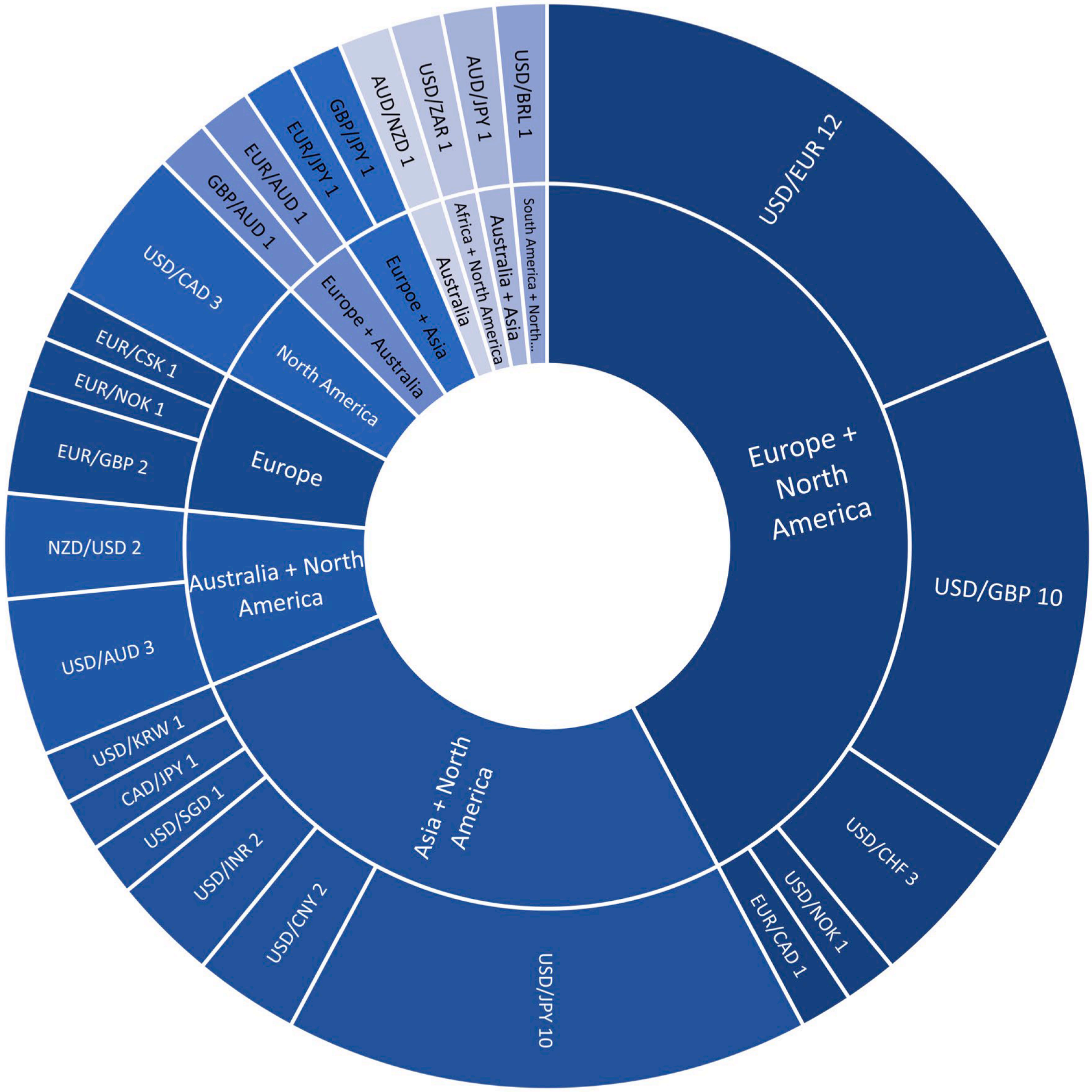

Fig. 5. Summary of predicted Forex rates **Source: A**uthor's Compilation.

generate profitable transactions by tuning in the right combination of selected features, training dataset size, and periodic retraining, as opposed to the complex models such as SVM and neural networks. Therefore, the authors employ-six simple machine learning models: One Rule, C4.5 Decision Tree, JRip, Logistic Model Tree, K Star, and Naïve Bayes to predict USD/JPY, EUR/GPB, and EUR/USD exchange rate's binary classification.

Machine learning models: SVM, Random Forest, and XGBoost are used to predict intra-day forex directional movements as bullish or bearish using text mining and sentiment analysis. XGBoost with Document Term Matrix and Forex Dictionary outperformed all other models in predicting the forex rates 30 min after a piece of economic news was released (Semiromi, Lessmann, & Peters, 2020). In a more recent study, the same models are used in addition to a 3-layered neural network for developing trading signals. The SVM and SVR model comprised radial basis function; for XGBoost, a maximum of 5 boosting iterations were applied, and 500 trees for Random Forest (Peng & Lee, 2021). A 3-layered perceptron (MLP) was trained to predict the foreign exchange rates of USD/EUR, JPN/USD, and USD/GBP on a daily, monthly, and quarterly time step (Galeshchuk, 2016).

Deep learning models such as LSTM forecast the forex rate by integrating the Forex Loss Function (Ahmed, Hassan, Aljohani, & Nawaz, 2020) or creating a hybrid model. Islam & Hossain (2020) model a hybrid GRU_LSTM, wherein the input data enters the GRU network and generates a weighted value sent to the LSTM network. Another set of weighted values is generated from the LSTM network and sent to a dense layer consisting of 64 neurons. The overall output is finally sent to a single neuron to compare with the actual output and optimize the weighted values. The proposed model surpasses the standalone GRU and LSTM models. Another hybrid CNN_LSTM model was created to gain the combined advantages of analysing time-series data (through LSTM) and feature extraction (through CNN). The proposed model was employed to predict profitable forex trading signals (Moghaddam & Momtazi, 2021).

An improved Deep Belief Network (DBN) was created to model continuous data by combining a DBN with Continuous Restricted Boltzmann Machines (CRBM) combined with conjugate gradient method to forecast weekly exchange rate and exchange rate return series. This model not only exceeds the FFNN concerning predictive accuracy but also provides higher stability (Shen, Chao, & Zhao, 2015). Table 7 summarises the exchange rates, datasets and source, models, study period, and tasks.

Adegboye & Kampouridis (2021) report the highest average accuracy at 81.7 % while predicting 20 forex rates. Here, the authors use AutoWeka for the directional change, which decides the optimal

Table 7
Financial application of machine learning in foreign exchange markets.

Title	Datasets/Source	Models	Features	Period	Performance Evaluation	Task
Shen, Chao, & Zhao (2015)	Respective Historical exchange rate, Weekly datasets from Pacific Exchange Rate Service	FFNN < Improved Deep Belief Network = continuous restricted Boltzmann machines + DBN	Past lagged observations of exchange rate	1976–1993, 1st January 2000 to 1st January 2004, 6th January 1994 to 10th July 2003	RMSE = 7.6900E-3, MAE = 6.0100E-3, MAPE = 0.9028, DA = 0.6362, Pearson correlation coefficient = 0.8817	Foreign Exchange rate prediction
Galeshchuk (2016)	Respective historical Exchange rates @ daily, monthly and quartely steps from Globalview and Oanda website	MLP	N/A	Daily: 01 Jan 2014 till 25 Apr 2014 Monthly: May 2009 till May 2014 Quarterly: May 1999 till May 2014	Average relative prediction error = 0.3 % and maximum relative prediction error = 1.3 %	Foreign Exchange rate prediction
Gerlein, McGinnity, Belatreche & Coleman, (2016)	Respective Historical exchange rate datasets @ hourly and daily	OneR, C4.5, JRip, Logistic Model Tree, KStar, Neural Networks, SVM and Naïve Bayes	Hour, day of the week, closing price, percentage of price change, lagged percentage of price change, lagged percentage of price change moving average (10 periods), relative strength index, Williams %R, class	**Training:** Wednesday, 02 January 2002 00:00:00–Friday, 29 December 2006 18:00:00 **Test set:** 2510 Thursday, 18 January 2007 12:00:00–Monday, 22 Jun 2009 00:00:00	Accuracy = 52.84 %, UP Accuracy = 54.58 %, Down Accuracy = 51.41 %, cumulative returns = 51.41 %, Maximum Drawdown = 52.34, Average return per trade = 22.42, Long_Accuracy = 0.0048 %, Short_Accuracy = 30.98 %	Prediction of exchange rate price direction-binary classification
Chandrinos, Sakkas, & Lagaros (2018)	N/A	ANN (multilayer FNN or deep neural network) and decision trees	20 indicators of which 14 are technical indicators	2006 to 2016	Sharpe ratio = 1.39	Risk Management in FOREX trades
Sun, Wang, & Wei (2019)	Daily data of the respective exchange rates from Wind database	Ensemble VMD-SVNN-SVNN	Exchange rate data series is subdivided using Variational decomposition in order to create k modes which become the input	January 1, 2011 to May 31, 2017	MAPE = 2.014 and Directional Symmetry = 59.94, Pesaran-Timmermann = 3.4605	Foreign Exchange rate prediction
Wei, Sun, Ma, Wang, & Lai (2019)	Daily data of the respective exchange rates from Wind database	Ensemble: VMD-SOM-KELM	N/A	3rd January 2011 to 29th December 2017	MAPE and Directional symmetry	Foreign Exchange rate prediction
Dash (2020)	Daily exchange rate prices	Recurrent Legendre Polynomial neural network + improved shuffled frog leaping (ISFL)	437 inputs based on 5 consecutive daily exchange rates	1/1/2014 to 31/5/2015	Average return per trade = 4.61 % and prediction accuracy = 58.965 %	Prediction of one day ahead Foreign Exchange rate, direction and develop trading strategies
Ahmed, Hassan, Aljohani & Nawaz (2020)	H4 candle data from XM broker	FLF - LSTM	Candle data: open, high, low, close price	June 2015 to Sep 2018	MAE = 1.50 × 10ˆ−3	Predicting the next 4 h candle (H4) for EUR/USD
Chanda, Bandyopadhyay, & Banerjee (2020)	Year-wise FDI, GDP, export–import, total expenditure plan, total expenditure on special plans import duty from Economic Surveys and Expenditure Budgets, Five Year Plan Documents, Data Books, Global Economic Prospects Reports by the World Bank; annual reports of RBI	ANN BP	Quantum of year-wise FDI inflows, Total exports, Total imports, Average import duty rate, GDP of the country, Total expenditure for all plan schemes of (DOC), Ministry of Commerce and Industry, GOI and Total expenditure for certain special schemes of the DOC	1989 to 2915	Error square = 0.000001, RMSE = 0.013098, Relative error square = 0.000049, Root mean square of relative error (RMSRE) = 0.086067	Forecasting Foreign Exchange reserve of a nation
Semiromi, Lessmann, & Peters, (2020)	Historical exchange rate prices dataset of 30 min interval from FXCM Micro Desktop client, Forex Factory website, Bloomberg and FX News (FIRS news)	XGB, SVM and random forest	Historical prices: Open, High, Low and Close for both the Ask and the Bid price, Technical indicators: simple moving average 10, 20, 40, MACD, Bollinger bands, custom, WILL, CCI, stochastic, RSI, SAR and trend line and News events	1st October 2015 to 31st October 2017	Accuracy = 60 %	Prediction of intraday forex directional movements

(*continued on next page*)

Table 7 (*continued*)

Title	Datasets/Source	Models	Features	Period	Performance Evaluation	Task
Islam & Hossain (2020)	per-minute data from Histdata website	GRU_LSTM Hybrid model = GRU + LSTM	Hour, Day, Week, Momentum, Average 566 price, Range, and OHLC price	January 1, 2017 to December 31, 2018 and January 1, 2019 to June 30, 2020 for 10 min and 30 min	MSE = 0.00084, RMSE = 0.02895, MAE = 0.01448	Predicting forex rates 10 mins and 30 mins before time
Arya Hadizadeh Moghaddam & Momtazi (2021)	Per-minute data	CNN for image processing and CNN_LSTM for prediction	Open, high, low, and close price data and candle stick image	March 1st, 2020 to July 31st, 2020	Precision = 0.3972, recall = 0.3963, macro average F1 = 0.3945, accuracy = 0.6395	Predicts profitability or non-profitability of a trading signal
Peng & Lee (2021)	Per-minute data from Dukascopy	SVM/SVR, random forest, XGBoost, and neural network	Spreads, changes in bid prices, changes in ask prices, differences in bid and ask volumes, volatility of bid prices, and ask prices	2007 to 2020	Accuracy = − 23.25 %, Path loss = 2.06 %	Developing two trading strategies in Forex market
Hassanniakalager, Sermpinis, & Stasinakis (2021)	Daily price (open, high, low, and close) and volume	Naïve Bayes, Bayesian regularized Neural Network	Signals generated by 7846 technical rules	2010 to 2016	N/A	Assessing the profitability of technical rules in forex trades
Adegboye & Kampouridis (2021)	10 min interval data from https://olsendata.com/	Selected by AutoWeka	6 variables related to Directional change and overshoot	March 2016 to February 2017	Accuracy = 0.817, Precision = 0.842, and Recall = 0.822	Predict when a trend will reverse
Lim, Jeong, Oh, & Lee (2022)	Daily closing prices from Seoul Money Brokerage Services, USDKRW exchange rate data collected by Yonhap Infomax and Bloomberg	Neural Network (MLP), XGBoost and Logistic Regression	Cross Currency Swap and Interest Rate Swap are independent variables and USDKRW exchange rate is the dependent variable	2003 to 2020	Annual return of 4.888 % ~8.464 %	Developing foreign exchange trading model
Farimani, Jahan, Fard, & Tabbakh (2022)	Hourly data from Finnhb REST API	RNN	14 variables (close price and 13 technical variables) + news sentiments	September 2018 to May 2021	MAPE = 0.122	Hourly Foreign Exchange rate prediction

Source: Author's Compilation.

classification algorithm for the given dataset. The need to select an algorithm for a specific task and tun the hyperparameter values for the selected algorithm is eliminated because the AutoWeka software automates the entire process. Semiromi, Lessmann, & Peters, (2020) achieve an accuracy of 64.4 % in predicting the intraday forex direction of EUR/USD and 60.5 % for USD/JPY. The study indicates better performance using SVM and Random Forest than XGBoost. Using the Hybrid CNN_LSTM model, **Arya Hadizadeh Moghaddam & Momtazi (2021)** . report an accuracy of 63.95 % in predicting the profitability of a trading signal. Based on the different performance evaluation metrics across the different applications of machine learning in the forex market, it is impossible at this stage to conclude which model is superior due to their low accuracy. Thorough research in this area should be carried out to compare different machine learning and deep learning models across various forex rates, and timestamps. There also lies scope in predicting the exchange rates of emerging countries.

4.5. *Financial crisis prediction*

Many financial crises have occurred in recent histories, such as The International Debt Crisis 1982, The East Asian Economic Crisis 1997–2001, the Russian Economic Crisis 1992–1997, The Latin American Debt Crisis 1994–2002, Global Economic Recession 2007–2009 to name a few. Financial crisis can be recognized as the outcome of the spread of financial disturbances through market linkages within economies. Previous literature identified these as a stock market crisis, sovereign bonds and credit default swaps (Samitasa, Kampourisb, & Kenourgios, 2020), sovereign debt crisis (Dawood, Horsewood, & Strobel, 2017), increasing risk in SMEs (Koyuncugil & Ozgulbas, 2012), fall in forex rates or currency crisis (Lin, Khan, Chang, & Wang, 2008) and more. Regional financial shocks can lead to a global financial crisis due to the increase in connectedness between countries. Quite logically, this explains why most studies choose to analyse a cluster of countries simultaneously and observe the flow of financial disturbances and their probable effects.

By using machine learning techniques, researchers have developed Early Warning Systems to anticipate financial crises ahead of time. This enables policymakers to formulate plans to limit the effects of financial crises and avoid any spillovers or negative turbulence which spreads across countries. The use of machine learning models in macroeconomic prediction includes predicting systematic banking crises, stock market crises, formation of financial bubbles, measuring volatility spillover, and detecting contagion risk.

4.5.1. *Features and datasets for financial crisis prediction*

Among the indicators used for predicting systematic banking crises are credit-related indicators, macroeconomic indicators (GDP), asset or property-related indicators (house price, property prices), and market-related indicators (interest rates). With regards to stock market turbulences, variables from stock markets, bond markets, exchange rates, and additional variables such as VIX index, oil prices, LIBOR rate, gold price, and more were selected (Chatzis, Siakoulis, Petropoulos, Stavroulakis, & Vlachogiannakis, 2018). In order to measure the flow of contagion risk within the financial network, weekly returns were calculated from 679 stock indices, 539 10-year sovereign bonds, and 420 5-year credit defaults across 33 countries from EU, Europe, Eurozone, Asia, Africa, North and South America (Samitasa, Kampourisb, & Kenourgios, 2020). The selection of variables has been complicated due to their non-availability in every country included in the sample. Details on the features used in each study are summarised in Table 8.

Training machine learning models to predict a crisis is confined to a particular definition associated with the dataset. For example, Tölö (2020) used the dataset of Jordà, Schularick, & Taylor (2017), which describes the financial crisis as "events during which a country's banking sector experiences bank runs, sharp increases in default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions" from 1870 to 2016, Dabrowski, Beyers & Pieter de Villiers (2016) used the dataset by Lainà, Nyholm, & Sarlin (2015), wherein crisis was defined as "the occurrence of simultaneous failures in the banking sector that

Table 8
Financial applications of machine learning in financial crisis prediction.

Title	Country/Zone	Datasets/Source	Features	Models	Train & test days	Performance evaluation	Task
Dabrowski, Beyers, & Pieter de Villiers (2016)	11 developed European countries (Austria, Belgium, Denmark, Finland, France, Germany, Italy, Sweden, Spain, United Kingdom and the Netherlands)	Quarterly data, Dataset by Lainà et al. (2015)	House prices, mortgages, mortgages to GDP, household loans, household loans to GDP, private loans, private loans to GDP, consumer price index, GDP, current account surplus to GDP, and loans to deposits	Dynamic Bayesian networks: hidden Markov model, switching linear dynamic system and the naïve Bayes switching linear dynamic system compared to logit model and signal extraction method	1980 to 2013	Precision = 0.67, recall = 1.00, F-score = 0.79 and accuracy = 0.67	EWS for systematic banking crisis
Michaelides, Tsionas, & Konstantakis (2016)	U.S.	N/A	Dividends, stock prices, equity prices, Stock price-dividend ratio etc. (not mentioned clearly)	Bayesian technique	January 1871 to June 2014	N/A	Detection of financial bubbles
Alessi & Detken (2018)	21 countries from the European Union	Quarterly Banking crisis dataset European Systemic Risk Board (ESRB) by Babecky et al. (2014).	30 variables from credit-related indicators, macroeconomic indicators, property prices and market-based indicators	Random Forest compared to logistic regression	1970–2010	AUROC = 0.93	Predicting Banking Crisis
Chatzis et al. (2018)	Asia, America, Europe and Globally	Stock price index, 10-year Govt bond yield of 39 countries, exchange rate of 18 currencies against USD, financial indices: oil, gold, VIX. Data from the FRED database and the SNL (S&P Global Market Intelligence) website	131 Variables from Stock markets, Bond markets, Exchange rates and Additional variable	Classification Trees, SVM, Random Forests, Neural Networks, CART, XG-Boost, Logistic regression and DNN	TRAIN: 1996–2010 TEST: 2011–2017	AUROC = 0.807, Kolmogorov Smirnov = 0.516, sensitivity and specificity, geometric mean = 0.682, positive likelihood ratio = 5.142, negative likelihood ratio = 0.537, Discriminant power = 1.246, Youden' s index = 0.417, Balanced Accuracy = 0.708 and Weighted Balanced Accuracy = 0.613	Predicting stock market crisis
Beutel, List, & Schweinitz (2019)	17countries = 15 European + Japan and U. S.	European System of Central Banks and European Systemic Risk Board by Lo Duca et al., 2017	10 variables from Asset prices, credit development, external & global imbalances, and macroeconomic environment	Logistic regression, k-NN, decision trees, random forests, SVM and neural networks	1970 to 2016	F-measure = 0.729, BPS = 0.132 and AUC = 0.880	Predicting Systematic Banking Crisis
Tölö (2020)	Australia, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, UK, Italy, Japan, Netherlands, Norway, Portugal, Sweden, and the USA	Jórda-Schularick-Taylor Macrohistory dataset 2012	5 variables: Loans to-GDP, house prices and stock prices, current account ratio, and real GDP	MLP with one hidden layer, LSTM and the GRU neural nets and logit model	1870–2016	AUC = 0.743	Predicting Systematic Banking Crisis
Samitasa et al. (2020)	Eurozone, European Union, Asia/pacific, Africa and America (33 countries in total)	Weekly data returns: for 679 stocks, 539 10-Year Bond Yield and 420 5-year CDS from Thompson Reuters DataStream	Centralities: betweenness, degree, eigenvector and closeness.	SVM, Decision tree	01/01/2004 to 31/12/201601/09/2006 to 31/12/201619/12/2008 to 31/12/2016	Overall Accuracy = 98.8 %	Detecting Contagion risk
Laborda and Olmo (2021)	U.S.	Daily sectoral closing prices of S&P 500 from Bloomberg	43 variables = the total volatility connectedness measure, 21 total directional volatility connectedness variables and 21 total net pairwise directional volatility connectedness variables	Random Forest and Decision Tree	July 20, 2003 to December 31, 2020	AUC = 0.98	Measuring volatility spillover
Ouyang et al. (2021)	51 institutions (22 Banks, 25 securities and 4 Insurance companies) China	Quarterly statements from WIND database	14 indicators from 4 categories: Institutional extremum risk, Contagion effects, Volatility and instability, Liquidity and credit risk	Attention-LSTM, LSTM, BP, SVR and ARIMA	January 2011 to December 2018	RMSE = 2.37 % and MAPE = e 1.1 %	Early warning of systematic financial risk

(*continued on next page*)

Table 8 (*continued*)

Title	Country/Zone	Datasets/Source	Features	Models	Train & test days	Performance evaluation	Task
Plessis (2022)	49 Countries	N/A	13 variables wrt real sector (4), banking sector (6), and external sector predictors (3)	ANN, gradient boost, k-NN, and random forests	1971 to 2017	True positive and accuracy rates = 85 % and the area under the receiver operating characteristics = 0.663	Tracking cyclical crisis formations
Petropoulos & Siakoulis (2021)	Central Banks of various countries	Speeches of the central Banks of various countries	Set of text documents consisting of central bank speeches	XGBoost > DNN, SVM, Random Forest	2008 to 2019	AUROC Coefficient = 78 %, Kolmogorov–Smirnov statistic = 57 %	Early warning system for financial market turmoil.

Source: Author's Compilation.

significantly impairs the capital of the banking system as a whole, which mostly results in large economic effects and government intervention." Alessi & Detken (2018) and Beutel, List, & Schweinitz (2019) use the datasets of Babecký, et al. (2014) and Duca, et al. (2017) respectively. For measuring volatility spill over, daily closing prices of sectoral indices of S&P 500 were used (Laborda & Olmo, 2021), and for predicting the stock market crisis, in addition to stock market indices, datasets of 10-year Govt bond yield of 39 countries, the exchange rate of 18 currencies and financial indices such as oil, gold, and VIX were used Chatzis et al. (2018).

4.5.2. Models for financial crises prediction

Common models used to predict financial crises in the past were based on logit models and signal extraction methods. Machine learning models belonging to the Bayesian Networks such as Hidden Markov Model, Switching Linear Dynamic system, and Naïve Bayes switching linear Dynamic system have outperformed the traditional logit model and signal extraction method (Dabrowski, Beyers, & Pieter de Villiers, 2016). These models have a drawback in their complex implementation; however, they effectively illustrate early warning systems.

Based on research comparing the performance of logit models and Random Forests, the authors report seeing similar results in both models when excluding the banking crisis of the 1970s and restricting the number of countries with similar financial and economic systems (Alessi & Detken, 2018). A comparative study contradicts these results, indicating that logit models consistently perform better than machine learning models: k-NN, Decision trees, Random Forest, SVM, and neural networks (Beutel, List, & Schweinitz, 2019). In a more recent study, the performance of deep learning models: RNN with LSTM and GRU surpassed the logit model and MLP at a single lag as well as at multiple lags (5) (Tölö,2020). Chatzis et al. (2018) empirically examined the performance of Random Forest, classification trees, SVM, XGBoost, neural networks, and deep FFNN with dropout regularization technique. Increasing classification accuracy is most easily accomplished via DNN. Furthermore, a shift from simple neural networks to deep networks benefit from richer and subtler dynamics in data, which increases the ability to model complex nonlinearities and cross-correlations among financial market variables. In another study, the performance of the attention mechanism based on the LSTM model has a higher accuracy rate than BPNN, SVR, and ARIMA model in predicting systematic financial risk and monitoring financial market changes (Ouyang, Yang, & Lai, 2021). The various machine learning techniques applied to time series data in order to predict financial crises were modelled using low-frequency data, as indicated in Table 8, with the exception of Laborda & Olmo (2021). Based on the previous literature reviewed, the use of deep learning models in financial crises is gaining the attention of researchers and is yet to be fully explored.

Concerning the performance evaluation of predictive models in this area, the average accuracy lies between 70 % and 80 % using Deep Neural Networks, LSTM, and Gradient Boosting. The SVM model reported the highest accuracy by Samitasa, Kampourisb, & Kenourgio (2020) at 98.8 %. This model is also supported by Gogas, Papadimitriou, & Agrapetidou (2018), who applied an SVM-based method to forecast the bankruptcy of U.S. financial institutions, achieving similarly high accuracy. Interestingly, these high accuracies are achieved on U.S. datasets; there is a need to test the performance of SVM models on datasets of other economies, especially emerging economies.

4.6. Insolvency and bankruptcy prediction

Attempts to predict the failure of firms began in the 1960 s with Beaver (1966), who described firm failure as "the inability of a firm to pay its financial obligations as they mature." This would include any of the following events: "bankruptcy, bond default, overdrawn bank account or non-repayment of preferred stock dividend." Matin, Hansen, Hansen & Mølgaard (2019) defined distress as a state of being "in

Table 9
Financial applications of machine learning in bankruptcy and insolvency prediction.

Authors	Country	Dataset/Source	Total Number of Firms	Features	Models	Time period	Performance metrices	Task
Iturriaga & Sanz, (2015)	U.S.	Historical data of banks financial statements published quarterly in Federal Deposit Insurance Corporation	772 (386 failed and 386 non-failed banks)	Importance of provisions, risk concentration on the construction industry and equity support to loans, interest expenses and deposits. Group3: overdue real estate loans and income to equity	Hybrid: MLP and Self Organising Maps	December 2002 to December 2013	Overall accuracy = 96.15 %, Precision = 94.44 %, Sensitivity = 98.08 % and Specificity = 94.23 %	Bankruptcy Prediction
Liang et al. (2016)	Taiwan	Taiwan Economic Journal	478 (239 bankrupt and 239 non-bankrupt)	190 inputs (95 Corporate Governance Indicators and 95 Financial ratios)	SVM, k-NN, Naïve Bayes classifier, classification and regression tree (CART) and MLP	1999–2009	Average prediction accuracy = 78 %, Type I error = 18.1 % and Type II error = 25.9/%	Bankruptcy Prediction
Tanaka, Kinkyo, & Hamori (2016)	OECD member countries	Financial statements from BankScope	18,381 (6,105 active banks and 6,105 inactive banks)	48 indicators from 4 categories: profitability ratio, capitalization, loan quality, and funding	Random Forest > decision tree and logistic regression	1986 to 2014	Accuracy rate = 82.48 %	Bank failure prediction
Antunes, Ribeiro, & Pereira (2017)	France	DIANE database and multiple credit risk datasets from UC Irvine machine learning repository (UCI)	1334 (Balanced 667–667) and 2000 (imbalanced 667–1333 and 400–1600) [Default-Healthy companies]	30 indicators	Gaussian Process, SVM and Linear Regression	2002 to 2006	Accuracy = 86.79 %, F1-score = 87.88 %, Precision 89.54 %, recall = 86.28 %	Bankruptcy Prediction
Barboza et al. (2017)	North America and Canada	NYU's Salomon Center database and Compustat	13,300 (133 bankrupt firms and 13,167 solvent firms)	11 variables out of which 5 are Altman variables	Bagging, Boosting, Random Forest, SVM with two kernels: linear and radial basis function, ANN, MDA & Logistic regression	1985–2013	AUC = 91.49 %, Accuracy = 85.5 %, Type I error = 21.09 % and Type II error = 14.44 %	Bankruptcy Prediction
Mselmi et al. (2017)	France	Annual financial data from DianeDatabase	212 (106 distressed and 106 non-distressed firms)	41 financial variables	hybrid SVM + Partial Least Squares outperformed Logit model, ANN (MLP), SVM Partial Least Squares	2010 to 2013	Overall accuracy = 0.9428, sensitivity = 0.9143, specificity = 0.9714, Type I error = 0.0811, Type II error = 0.0303, the AUCROC = 0.9429, and Kappa statistic = 0.8857	Financial Distress Prediction
Veganzones & Séverin (2018)	France	Balance sheets and income statements of French firms from Altares database	1500 firms (50/50, 60/40, 70/30, 80/20, 90/10, and 95/5 ratio of non-bankrupt/bankrupt)	Out of 50 variables, 9 to 10 variables are selected for each sector	Statistical Models: LDA and logistic regression, Neural Networks, Random Forest and SVM	2013 and 2014	Sensitivity = 79.2 %, Specificity = 80 %, G-mean = 79.2, and area under the receiver operating characteristic (ROC) curve AUC = 68.0 %	Bankruptcy Prediction
Le & Viviani, (2018) .	U.S.	Financial Statements from Bankscope database	3000 (1438 failures and 1562 active banks)	31 ratios	ANN and k-NN outperform SVM, LDA and Linear Regression	2008 to 2014	Precision = 75.7 %, Recall = 75.3 %, ROC Area = 81.9 %, PRC Area = 80.3 %	Bank Failure Prediction
Gogas, Papadimitriou, & Agrapetidou, (2018)	U.S.	Financial statements	1443 (962 solvent and 481 failed banks	36 ratios	SVM	2007–2013	Accuracy = 99.22 %	Bank Failure Prediction
Hosaka (2019)	Japan	Standalone Balance sheets and profit-and-loss statements	2164 (102 companies delisted and	Financial ratios converted to image	CNN based on GoogleNet outperforms	January 2002 to June 2016	Identification of bankruptcy rate = 86 %	Bankruptcy Prediction

(*continued on next page*)

Table 9 (*continued*)

Authors	Country	Dataset/Source	Total Number of Firms	Features	Models	Time period	Performance metrices	Task
		from Nikkei NEEDS Financial QUEST database	2062 listed companies on Japan stock market)		CART, LDA, SVM, Decision Tree, MLP, AdaBoost and Altman's Z Score			
Son, Hyun, Phan, & Hwang, (2019)	Korea	Financial ratios from NICE Information Service Co. (a Korean credit rating agency)	977,940 (23,137 bankrupt and 954,803 non-bankrupt)	130 features	Linear Regression, Random Forest, Gradient Boosting (XGBoost, LightGBM) and ANN	2011–2016	AUC = 0.88	Bankruptcy Prediction
Mai et al. (2019)	U.S.	Annual Accounting data from Compustat North America, Daily and monthly Equity trading data from Center for Research in Security Prices (CRSP) and textual disclosure data from10-K annual filings to *SEC*	11,827 (477 bankruptcy filings and 11,350 no filings)	36 variables	CNN	1994 to 2014	Area under the ROC curve (AUC) = 0.842 %	Bankruptcy Prediction
Climent, Momparler, & Carmona (2019)	Eurozone	Orbis database	155 (43 received state aid and 112 have not	25 financial ratios frm 5 categories (Asset Quality, Operating ratios, capital ratios, liquidity ratios and balance sheet)	XGBoost	2006 to 2016	AUC = 0.817	Bank Distress Prediction
Carmona, Climent, & Momparler (2019) .	U.S.	Annual data from Federal Deposit Insurance Corporation database	156 (78 failed banks and 78 non-failed banks)	30 financial ratios	XGBoost outperforms Linear Regression and Random Forest	2001 to 2015	AUCROC = 0.875 and Accuracy = 92.11 %	Bank Failure Prediction
Matin et al. (2019)	Denmark	Auditors' reports and managements' statements from Annual reports from Danish Central Business Register	278 047 firm years (112 974 unique firms and 8 033 distresses)	50 financial variables	LSTM + CNN + RNN	2013–2016	AUC = 0.879 and Log score = 0.0611	Corporate distress prediction
Huang & Yen (2019)	Taiwan	Taiwan Economic Journal Database	64 (32 financially-distressed and 32 non-distressed firms)	16 variables	SVM, hybrid Genetic Algorithm-fuzzy clustering and XGB, DBN and DBN-SVM	2010 to 2016	Accuracy	Financial distress prediction
Zoricák, Gnip, Drotár, & Gazda (2020)	Slovak Republic	Annual Reports	Year-wise observation (98 % non-bankrupt and 2 % bankrupt)	20 financial ratios	SVM	2010–2016	Geometric mean score = 91.54 %, ROC AUC = 91.83 %	Bankruptcy Prediction
Manthoulis et al. (2020)	U.S.	Reports of Condition and Income (Call Reports) and Uniform Bank Performance Reports from Federal Financial Institutions Examination Council. Data on failed banks from FDIC	6500 (6070 non-failed banks and 430 failed banks)	13 indicators = 6 indicators based on CAMELS and 1 size indicator. And 6 diversification indicators	Linear Regression SVM, Random under-sampling boosting	2006–2015	Area under ROC = 96.85 % and Kolmogorov Smirnov distance = 84.70 %	Bankruptcy Prediction
Petropoulos, Siakoulis, Stavroulakis & Vlachogiannakis (2020)	U.S.	Quarterly information from FDIC	175,000 obs. approx	Out of 660 Variables based on CAMELS 23 were selected	LDA, Random Forest, SVM, Neural Networks and Random Forest of Conditional Inference Trees	2008 to 2014	G-mean = 0.9183, Negative Likelihood ratio = 0.1511, Discriminant power = 3.6619, Balanced Accuracy =	Insolvency Prediction

(*continued on next page*)

Table 9 (*continued*)

Authors	Country	Dataset/Source	Total Number of Firms	Features	Models	Time period	Performance metrices	Task
							0.9210, Youden's index = 0.8421, and AUR ROC = 0.9886	
Jardin (2021)	France	Balance sheets and Income statements from database of Van Dijk	20,000 (19,600 non-failed firms and 400 failed firms)	30 ratios from liquidity, solvency, profitability, financial structure, activity and rotation	Logistic regression, decision tree (CART), k-NN, BPNN, SVM and ELM. Ensemble model: Self Organizing Neural Networks	2006 to 2016	Overall correct classification, Differences (percentage points) between correct classification rates	Bankruptcy & Financial Health (degree of financial soundness)
Jabeur, Gharib, Mefteh-Wali, & Arfi (2021)	France	Data from Orbis database	133 companies bankrupt	18 ratios wrt profitability, liquidity and solvency	Discriminant analysis, the logistic regression, SVM, neural networks, random forest, gradient boosting, DNN, XGBoost	2014–2016	Accuracy = 82.9 % and ROC curve (AUC) = 0.764	Bankruptcy Prediction
Jardin (2021)	France	Balance sheets and income statements from the Diane database	30,000 (29,400 non-failed and 600 failed)	20 financial ratios wrt profitability, liquidity, solvency, activity, financial structure, turnover	SVM, bagging, boosting with AdaBoost, random subspace, random forest and XGBoost	2000 and 2016	Correct classification rates 81.96 %, F2-scores = 81.62 % and AUC = 0.819	Bankruptcy Prediction
Garcia (2022)	U.S.	Quarterly data collected from Bloomberg	1824 U.S. firms (47 firms experienced bankruptcy)	9 variables	Boosted logistic regression, LDA, Naïve Bayes, K-NN Neural net, SVM, XGB machine, Random Forest, Random Forest ensemble	January 2010 to December 2018	Precision = recall = specificity = G-mean = F-measure = AUC classification accuracy = 1.00	Bankruptcy Prediction
Wu, Ma, & Olson (2022)	China	Financial statement data of companies listed on Shenzhen and Shanghai stock exchanges from CSMAR database	293 financially distressed companies and 16,913 financially healthy companies	5 ratios: ratio of working capital to total assets, ratio of retained earnings to total assets, ratio of EBITDA to total assets, ratio of market value of equity to total liabilities, ratio of sales to total assets	Multi-layer perceptron	2016 to 2020	Average correct classification rate = 99.40 %	Enterprise crisis warning

Source: *Author's Compilation.*

bankruptcy, bankrupt, in compulsory dissolution or ceased to exist following compulsory dissolution." According to a study on small and medium firms in France, firms with event declarations filed during the testing period with the judicial tribunal of commerce were considered distressed (Mselmi, Lahiani, & Hamza, 2017).

The reviewed literature includes assorted studies related to these definitions and covers the domains of bankruptcy prediction, insolvency prediction, corporate distress prediction, and bank failure prediction. It is evident from Table 9 that a majority of the studies from the existing literature are based on firm bankruptcy prediction compared to banks.

4.6.1. *Features used for insolvency and bankruptcy prediction*

In an attempt to determine the usefulness and empirical analysis of ratios, Beaver (1966) selected the activity of predicting failure of firms, followed by Altman (1968), who assessed the quality of ratios as an analytical technique by illustrating corporate bankruptcy prediction. From then on, the use of these ratios became a crucial variable in predictive bankruptcy models.

Son, Hyun, Phan & Hwang (2019), Matin et al. (2019), Mselmi et al. (2017) employed a large number of financial ratios or indicators to train the model. However, utilizing plenty of variables to train a model may result in a very high dimensional feature-space, reducing the model's predictive ability (Veganzones & Séverin, 2018). A feature selection process can be implemented to include only those variables that are most relevant. Petropoulos, Siakoulis, Stavroulakis & Vlachogiannakis (2020) selected the most relevant features from 660 variables by adopting a four-step process that excluded variables correlated to the dependent variable followed by cross-correlation analysis. To evaluate the explanatory power of the remaining variables, LASSO was administered, followed by a permutation statistic calculation which finally led to the selection of 23 financial ratios. Veganzones & Séverin (2018) used a two-step selection process to reduce the feature inputs for each sector under study.

In addition to the financial ratios, inevitably used to train machine learning models, corporate governance indicators have proven to improve bankruptcy prediction of Taiwan companies (Liang, Lu, Tsai, & Shih, 2016). From amongst the corporate governance indicators, broad structure and ownership structure coupled with financial ratios of solvency and profitability have demonstrated significant results in bankruptcy prediction. Another study attempted to convert a set of financial ratios into grayscale images, which were then used as inputs to train the CNN model (Hosaka, 2019).

With relevance to bank default prediction, the indicators widely used are based on the CAMELS framework, which is the abbreviation for Capital adequacy, Asset quality, Management efficiency, Earnings, Liquidity, and Sensitivity to market risk (Petropoulos, Siakoulis, Stavroulakis, & Vlachogiannakis, 2020, Gogas et al., 2018). However, these indicators focus on the bank's financial characteristics and fail to capture the risk involved in its operational and strategic functioning. To address this issue, Manthoulis, Doumpos, Zopounidis, & Galariotis (2020) adopted 6 diversification variables related to interest income, total income, expenses, earning assets, loan portfolio, and deposits, along with CAMELS indicators.

The financial ratios were computed from the financial statements of the respective firms/banks. These usually consisted of the Balance Sheet and Income statement or Profit & Loss Account. In order to predict financial distress more accurately, text-based data was used from auditors' reports and managements' statements (Matin et al., 2019) and 10-K annual filings to *SEC* (Mai, Tian, Lee, & Ma, 2019). Details on datasets and sources, industry, number of firms/banks, and features are depicted in Table 9.

A significant problem encountered while applying machine learning techniques in bankruptcy prediction was an imbalanced dataset. The number of firms/banks that are non-bankrupt significantly outrepresent those that are bankrupt. When a model is trained with such a highly imbalanced dataset, it tends to make a biased decision. To address this issue, a study was conducted by training models with datasets consisting of different proportions of non-bankrupt and bankrupt firms: 50/50, 60/40, 70/30, 80/20, 90/10, and 95/5. The study revealed that bankrupt firms which represent less than or equal to 20 % of the total sample space suffer from declining predictive performance (Veganzones & Séverin, 2018). Therefore, an increase in imbalance decreases the performance. Zoricák, Gnip, Drotár, & Gazda (2020) utilized a one-class classification method that trains the model with samples only from the majority class, and the aberrant data points from the test data are identified as bankrupt firms.

4.6.2. Models used for insolvency and bankruptcy prediction

Some of the notable works in the area of failure/bankruptcy/financial distress of firms include those of Beaver (1966), who employed a univariate model for predicting firm failure, followed by Altman (1968), who illustrated bankruptcy prediction through Multi Linear Discriminant Analysis, followed by Ohlson (1980) utilizing the logit model for corporate failure prediction and Zmijewski (1984) who utilized the Probit model for predicting financial distress. These models serve as a benchmark for comparing the current machine learning models. The machine learning models employed in this financial domain include classification, clustering, ensemble methods, deep learning, and reinforcement learning models. Most studies compare the performance of their proposed model to statistical models such as Linear Regression, LDA, MDA, and Altman's Z score. In all such comparative studies, machine learning models have outperformed these statistical techniques. Very few studies examined the performance of a single machine learning model or a hybrid model, while most studies focused on determining the most accurate one from a pool of machine learning models.

SVM models were implemented in many studies to classify firms/banks based on their performance. However, Zoricák, Gnip, Drotár & Gazda (2020) pointed out that the standard deviation obtained using this model on imbalanced datasets was very high and dissuaded its use as a reliable approach in predicting bankruptcy. In contrast to this opinion, Liang et al. (2016) appraised the performance of SVM combined with Stepwise Discriminant Analysis, which outperformed k-NN, Naïve Bayes classifier, CART, and MLP. On the same lines, Mselmi et al. (2017) employed a hybrid SVM_PLS model, which outperformed the

Fig. 6. Application – model heatmap. **Source:** Author's compilation.

logit model, MLP, individual SVM and PLS techniques. Adding to the discussion on the superiority of models, SVM does perform better than statistical models such as MDA, Linear Regression, and ANN. However, SVM causes more misclassifications when compared to other machine learning models such as Random Forest, bagging, or boosting. In such a case, Random Forest is regarded to have better accuracy and error rates (Barboza, Kimura, & Altman, 2017). The superiority of Random Forest in predicting bank insolvency is indicated in yet another study that consistently outperforms other machine learning and statistical models (Petropoulos, Siakoulis, Stavroulakis, & Vlachogiannakis, 2020).

A CNN model based on GoogleNet was trained using grayscale images to predict bankruptcy. The proposed model surpassed the performance of MLP, AdaBoost, CART, SVM, LDA, and Altman's Z score. The drawback of this model lies in its inability to determine the financial ratios that would strongly influence bankruptcy and hence fails to investigate the cause of the same (Hosaka, 2019).

The highest accuracy was reported by Wu, Ma, & Olson (2022) using MLP. The authors achieved an Average correct classification rate of 99.40 %. The authors use five financial ratios to train the model (see Table 9). Gogas et al. (2018) applied an SVM model to separate the solvent banks from the failed banks, achieving an accuracy of 98.25 %. Interestingly, majority of the studies in the area of insolvency and bankruptcy prediction have achieved an accuracy of above 75 % using different machine learning, deep learning and Hybrid models.

5. Analysis and discussion

5.1. Application–model analysis

Fig. 6 illustrates the application-model heatmap that indicates various machine learning models across the financial applications covered in this literature survey. It indicates that SVM models have been most frequently used, especially in insolvency and bankruptcy prediction. This is mainly because of its effectiveness in dealing with two-group classification problems. Many studies have also applied this supervised machine learning model in the stock market and cryptocurrency studies. Classical machine learning models such as k-NN, Bayesian networks, and decision trees have been scarcely used since 2015 to the present. Moreover, deep learning models: ANN, MLP, FFNN, BPNN are overwhelming predictive models, especially in stock markets. The applications of various neural networks such as CNN, RNN, GRU, and reinforcement learning are presently limited in financial fields but are yet a work-in-progress. Forex, insolvency/bankruptcy, and financial crisis prediction have minimal use of these deep learning techniques compared to machine learning. Hybrid and ensemble models are being used in recent years despite the many complexities in their implementation. A deeper understanding of their capabilities requires further research.

5.2. Validation approaches

A validation dataset is a sample of data held back from training the model to estimate the model's skill while tuning the hyperparameters. Hence proper validation is essential in running a machine learning model. While reviewing these articles, we find that some authors have interchangeably used the terms "validation set" and "test set". It is important to understand that the validation dataset is a sample of data held back from the training dataset and not the test set itself. Of the 126 articles selected for review, 43 articles do not mention using a validation set. Out of the remaining 83 articles applying validation approaches, 16 do not specify the method applied. The results indicate that the "10-fold cross-validation" is most commonly applied in five of the six financial areas that leave behind portfolio management. This validation technique is primarily used in insolvency and bankruptcy. The "10-fold

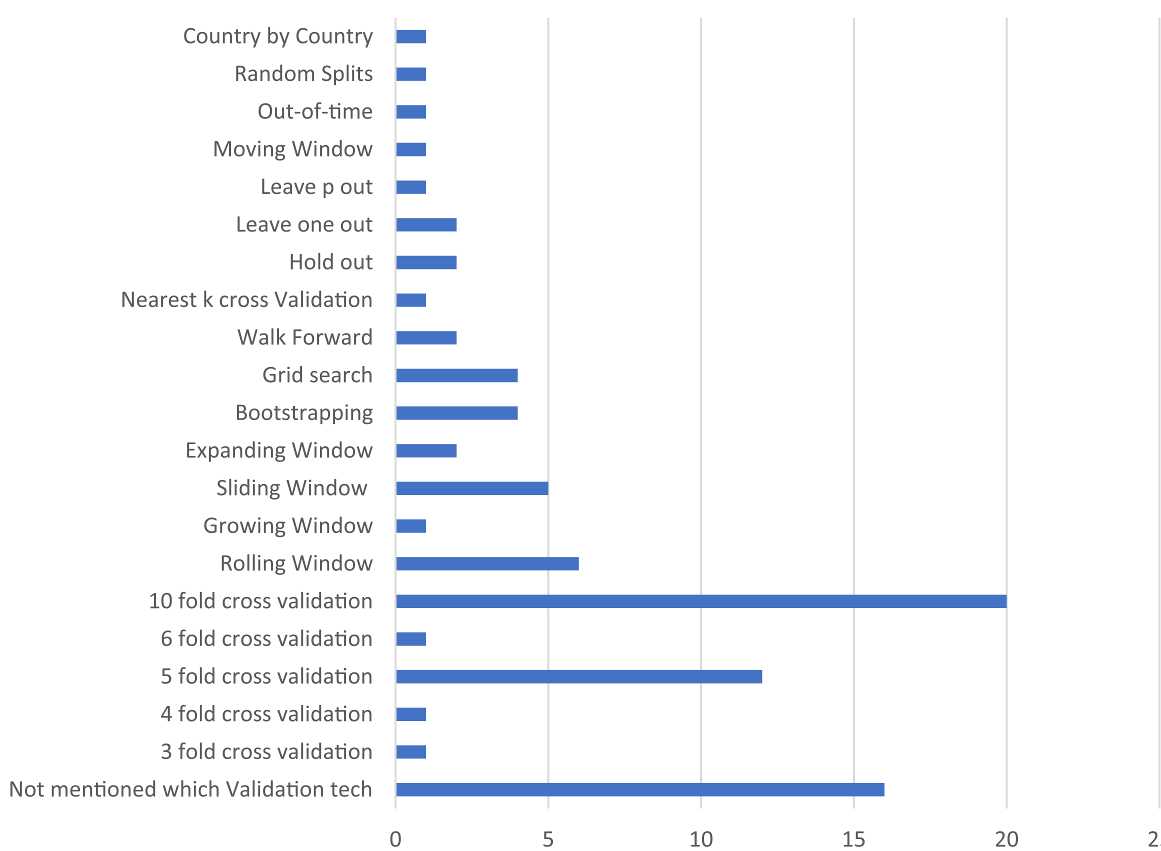

Fig. 7. Validation Approaches. **Source:** Author's compilation.

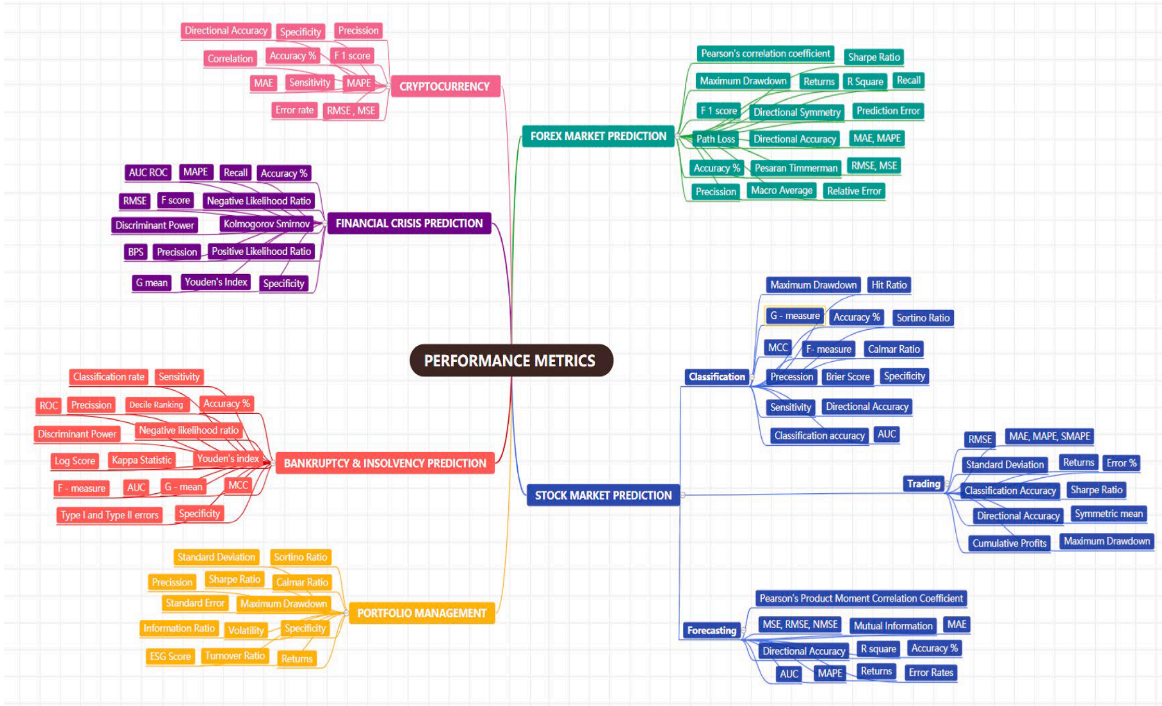

Fig. 8. Performance metrics map **Source:** Author's compilation.

cross-validation" method is applied in 24 % (20) studies. Similar results are witnessed in "5-fold cross-validation", which was applied in 14 % (12) studies, mainly used in stock markets. The "Rolling-window" and "Sliding Window" are applied in 7 % (6) studies and 6 % (5) studies, respectively. "Grid search" and "Bootstrapping" are each applied in 5 % (4) studies. "Expanding Window", "Walk Forward", "Leave one out", and "Holdout" methods are applied in 2 studies each. A few validation techniques are applied to a single study and can be inferred from Fig. 7.

5.3. Performance metrics analysis

In order to judge the performance of machine learning models or compare their performance to other models, specific evaluation metrics are calculated. The same has been mapped in Fig. 8 across the six financial applications. Machine learning models in stock markets were used for predicting direction, price, and developing trading strategies which are depicted as a bifurcation in the figure since different metrics are to be used for different tasks.

Performance of regression models (predicting a numeric value) are evaluated based on error metrics: MSE, RMSE, NMSE, MAPE, MAE. These are mainly used to predict stock or cryptocurrency price/return and forex rate/return. In addition, a classification model's performance (predicting the direction) is evaluated using classification accuracy, precision, recall/sensitivity, and F1 score, AUC, ROC, Hit ratio, MCC, negative likelihood ratio, positive likelihood ratio, Kolmogorov Smirnov, that are derived from confusion matrix made up of true positives, false positives, true negatives, and false negatives. Brier score is used for evaluating probability prediction. G-mean is used explicitly on imbalanced datasets (wherein the number of bankrupt firms is much less than non-bankrupt firms and in financial crises that do not happen frequently).

Model predictive performance cannot be guaranteed in the real world based on these metrics alone. Thus, financial metrics are essential to evaluate the effectiveness of machine learning models in financial domains. These include the Calmar ratio, Sortino ratio, Sharpe ratio, turnover ratio returns (annual, mean), and cumulative profits used extensively in the stock market and forex trading and portfolio management.

5.4. Software/programming languages

Fig. 9 depicts various software/programming languages for

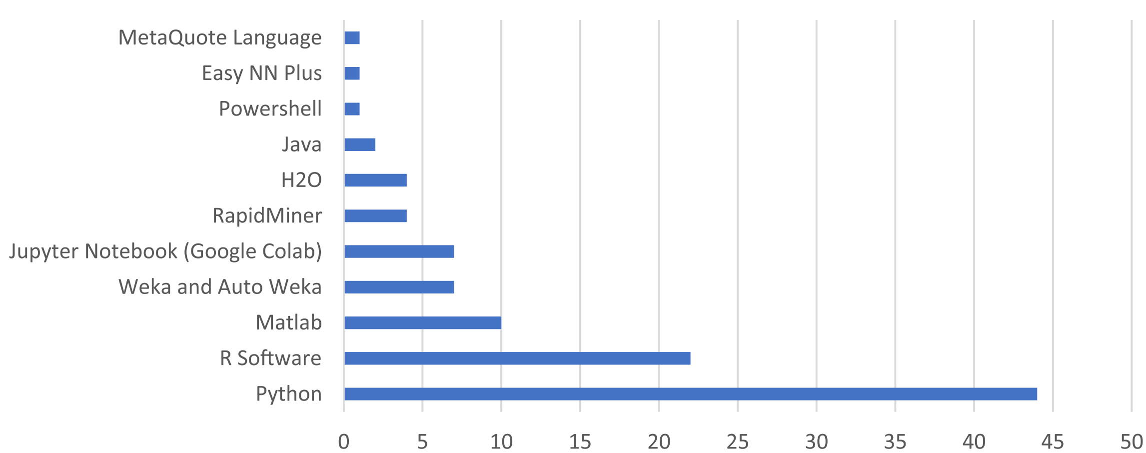

Fig. 9. Software/Programming Languages. **Source:** Author's compilation.

developing, training, and testing machine learning and deep learning models. From the literature reviewed, Python is the most preferred programming language used in 44 studies. It is a general-purpose programming language offering higher flexibility compared to non-programming software while running machine learning models. R is another popular software used in application development. This software is adopted by 22 studies, followed by ten studies that use Matlab software. Seven studies each use Weka (Auto Weka) and Jupyter Notebook, including Google Colab. RapidMiner, H2O, and Java are other software tools and programming languages that are rarely used. The most common libraries used in building and training models are Keras, TensorFlow, and Scikit Learn.

5.5. Year-wise publication analysis

Fig. 10 illustrates an ongoing increase in research articles published recently in the field of finance. Moreover, the publication of researcher articles significantly increased in 2019, and whereas publications in the last two years showed a steady increase. The number of articles published in 2022 is depicted only until 30th July, when the research articles were extracted. Despite this, Fig. 10 indicates that the number of articles published in 2022 has already surpassed more than two-third the number of articles published the entire year of 2021. This shows an increasing interest of researchers in implementing machine learning techniques in finance.

Fig. 11 depicts the number of articles published annually from 2015 to 2022 across stock market prediction, portfolio management, cryptocurrency, forex prediction, financial crisis, and insolvency and

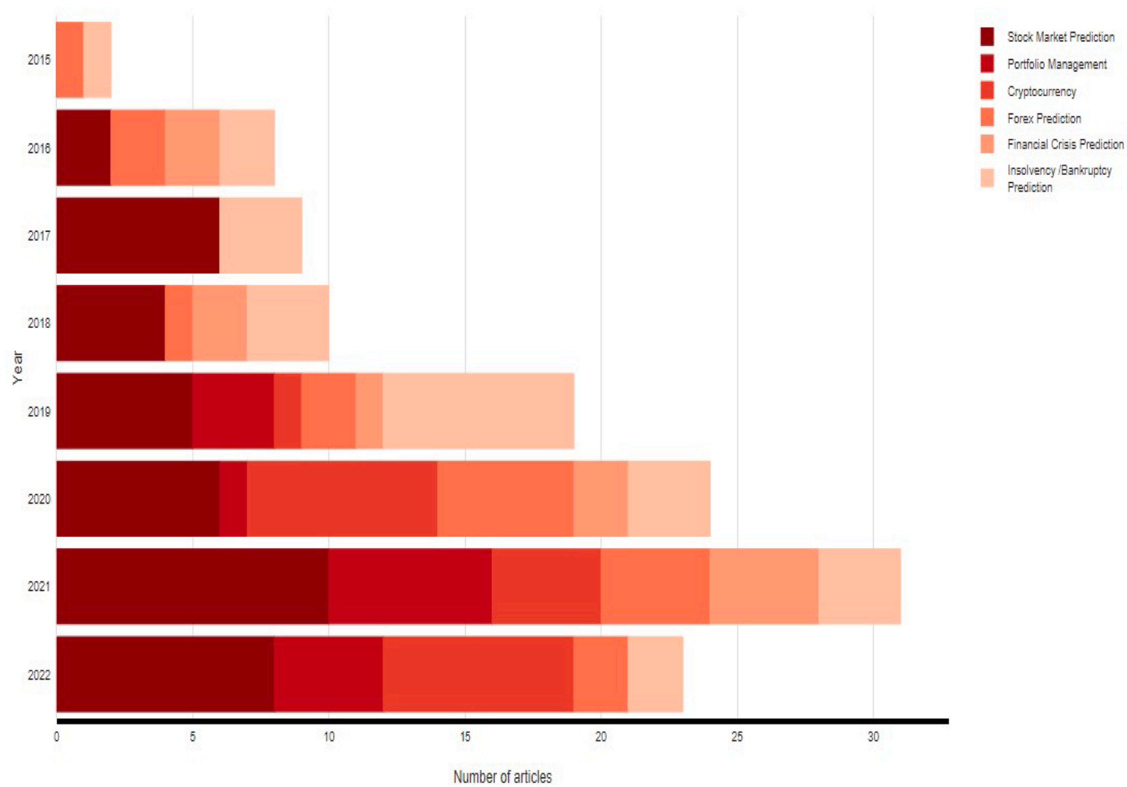

Fig. 10. Year-wise stacked publication analysis. **Source:** Author's compilation.

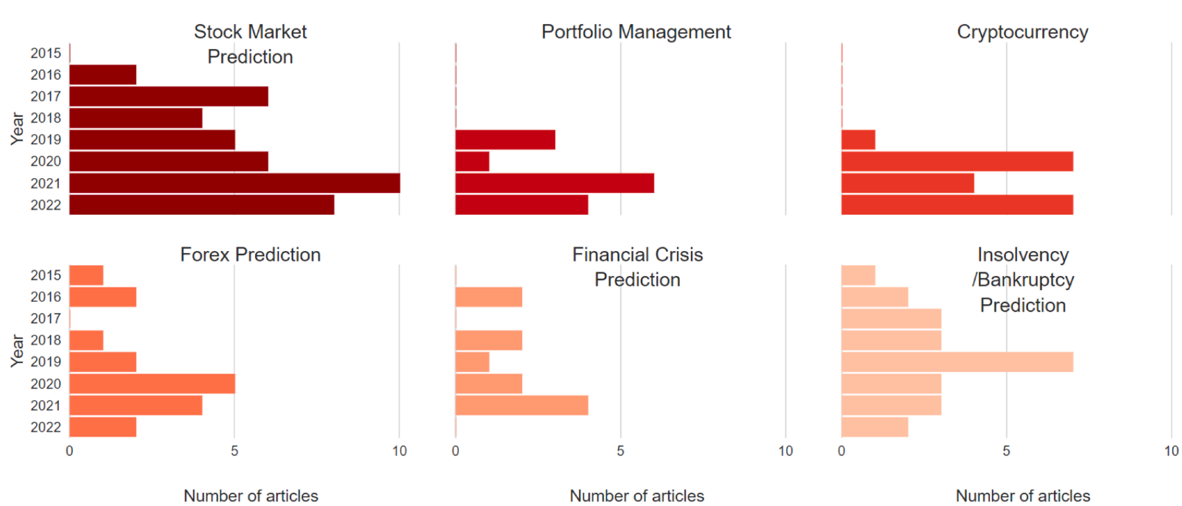

Fig. 11. Year-wise publication analysis across each application. **Source:** Author's compilation.

bankruptcy prediction. Articles on portfolio management using machine learning seem to spark interest amongst researchers over the last four years. Meanwhile, although cryptocurrencies existed more than a decade ago, researchers have recently begun predicting their future prices using machine learning. While only a few studies attempt to predict the financial crisis, areas such as the stock market, cryptocurrency, and portfolio management have increasingly used machine learning models. Overall, we conclude a growing trend of applying machine learning tools in the surveyed financial areas.

5.6. Journal-wise publication analysis

The 126 articles under review were published across 44 journals sourced from the ScienceDirect database and are depicted in Fig. 12. *Expert Systems With Applications* had the highest number of publications of articles on Machine Learning in finance. Additionally, the sole journal consisted of articles from all six financial applications reviewed in this study. Next, 12 research articles were published in *Applied Soft Computing Journal* across all domains except for the financial crisis. 6 papers followed this in the *European Journal of Operational Research.* 5 articles each were published in each of the following three journal*: Machine Learning with Applications, Finance Research Letters*, and *Decision Support Systems.* 4 papers each were published in the *The Journal of Finance and Data Science*, *International Journal of Forecasting, Knowledge-based Systems* and *Journal of Financial Stability.* The *Journal of Financial Stability* consisted of 4 articles solely based on the financial crisis.Fig. 13.

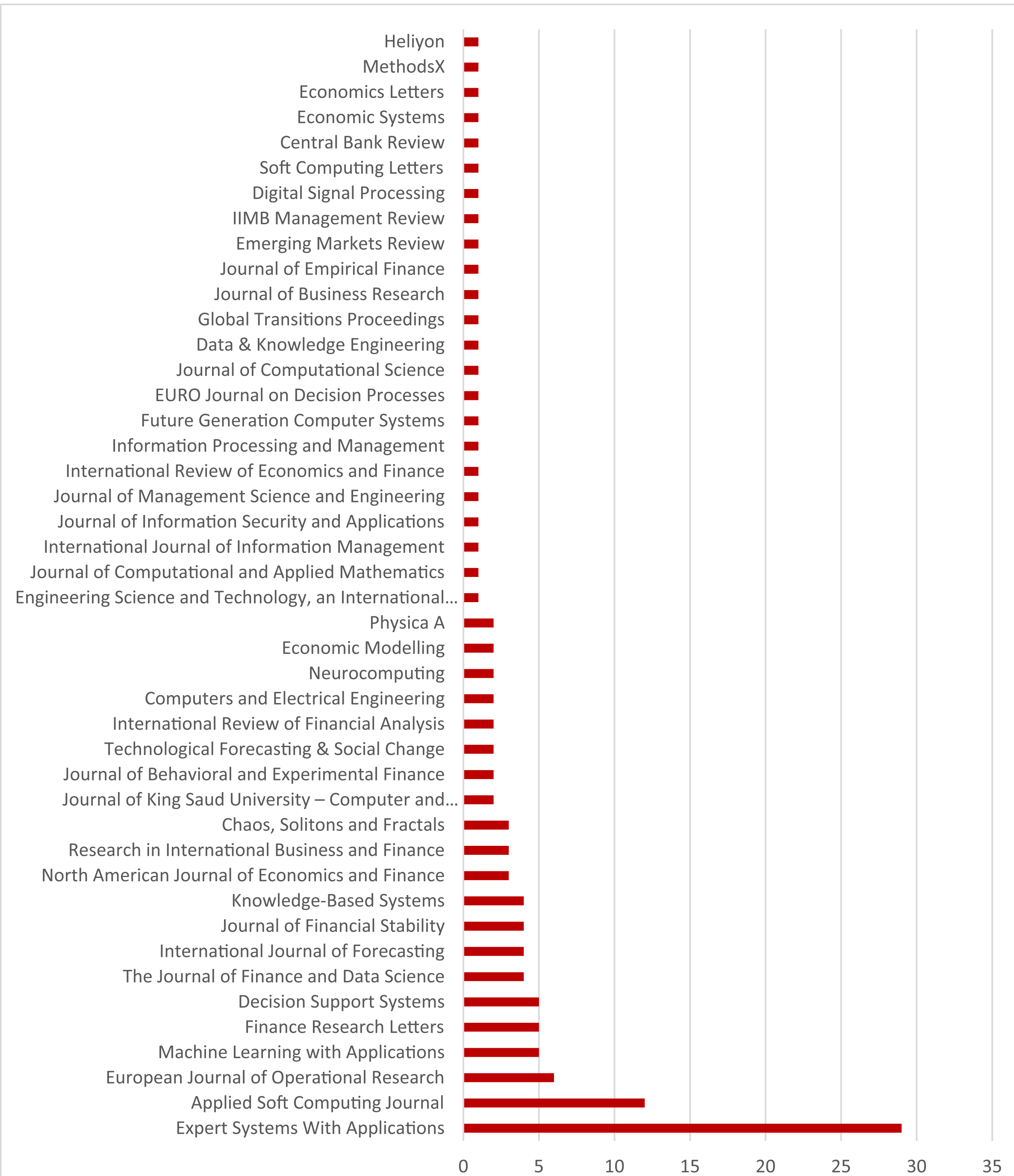

Fig. 12. Publication distribution across journals. **Source:** Author's compilation.

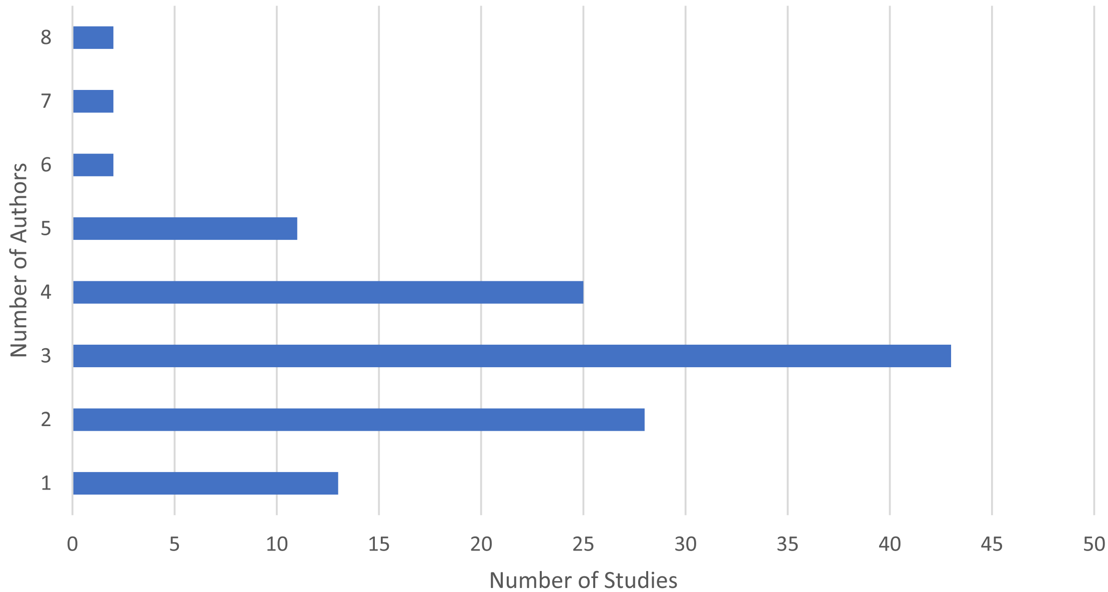

Fig. 13. Number-wise contribution of authors. **Source:** Author's compilation.

North American Journal of Economics and Finance, Research in International Business and Finance, and Chaos, Solitons and *Fractals* consists of 3 research articles published in each journal. Eight journals namely; *Journal of King Saud University – Computer and Information Sciences, Journal of Experimental and Behavioral Finance, Technological Forecasting & Social Change, International Review of Financial Analysis, Computers and Electrical Engineering, Neurocomputing, Economic Modelling, and Physica A* consists of 2 research articles per journal. Out of the 44 journals, 1 article each was published in 23 journals, namely: *Engineering Science and Technology, an International Journal, Journal of Computational and Applied Mathematics, International Journal of Information Management, Journal of Information Security and Applications, Journal of Management Sciences and Engineering, International Review of Economics and Finance, Information Processing and Management, Future Generation Computer Systems, EURO Journal on Decision Processes, Journal of Computational Science, Data and Knowledge Engineering, Global Transitions Proceedings, Journal of Business Research, Journal of Empirical Finance, Emerging Markets Review, IIMB Management Review, Digital Signal Processing, Soft Computing Letters, Central Bank Review, Economic Systems, Economics Letters, MethodsX, and Heliyon.* Although this study is an interaction between two diverse branches, i.e., computer science and finance, majority of the studies were published in computer science journals.

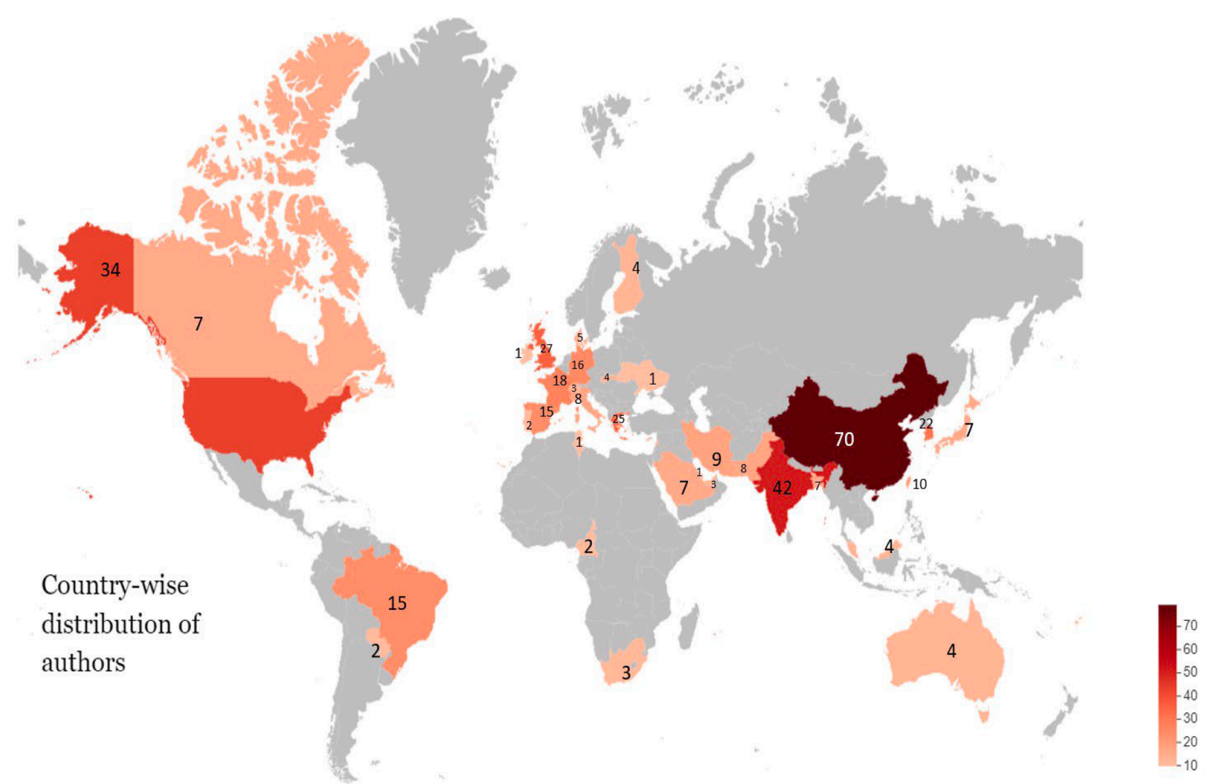

Fig. 14. Country-wise contribution of authors. **Source:** Author's compilation.

5.7. Number-wise contribution of authors

Of the 126 articles, 13 are single-authored documents, and 113 are multi-authored documents. Most articles, i.e., 43, are authored in groups of 3 authors. Furthermore, groups of two authors published 28 articles each group. 25 articles were authored by groups of 4, followed by 11 articles authored by a group of five authors. In addition, 1 article was authored by groups of six, seven, and eight authors. There are 395 authors across the 126 reviewed articles, of which 16 authors were involved in the publication of two research articles selected under this review.

5.8. Country-wise contribution of authors

The geographical map depicted in Fig. 14 indicates the quantum of articles published by authors from different countries concerning the financial applications of machine learning. 395 authors from 40 different countries published 126 research articles. China has dominated research in this area with 70 authors, which covers a little less than a fifth of the total number of authors. Authors from India and U.S.A are the following highest contributors, with 42 and 34 authors, respectively. Furthermore, there have been impressive contributions in this research field from countries such as U.K. (27 authors), Greece (25 authors), South Korea (22 authors), France (18 authors), Germany (16 authors), Brazil and Spain (15 each), and Taiwan (10 authors). 9 authors follow this from Iran, 8 each from Italy and Pakistan, and 7 authors each from Japan, Bangladesh, Canada, and Saudi Arabia; contributing their expertise in this area. A few authors from countries such as, Denmark, Australia, Finland, Malaysia, Slovak Republic, South Africa, Switzerland, UAE, Argentina, Cameroon, Fiji, Paraguay, Portugal, Bahrain, Cyprus, Ethiopia, Ireland, Qatar, Tunisia and Ukraine are emerging as researchers in this field.

6. Conclusion

The present study reviews and examines recent literature on the convergence of two diverse fields; machine learning, a branch of computer science, and its applications in finance. As the use of machine learning in finance is ever-growing, we review in detail six main applications that demonstrate the power of this technology. These applications include stock market prediction, portfolio management, cryptocurrency, forex market, financial crisis, and bankruptcy and insolvency prediction. 126 articles were reviewed and analysed across 44 reputed journals sourced from the ScienceDirect database published since 2015. The current work exhibits a brief discussion on the features, datasets, validation approaches, models, and performance metrics used across each financial application, followed by an analysis of the existing literature on hand.

The application of machine learning in stock markets is overwhelming, and their effective predictive performance has disproved the Efficient Market Hypothesis theory. The study identifies the use of this technology in predicting stock prices, stock direction, stock volatility, market indices, and returns forecasting. ANN (MLP) with FFNN or BPNN were most frequently used in predicting stock markets, followed by Random Forest and SVM. In order to enhance predictive performance, not only are historical prices and technical indicators used as inputs to train the models, but machine learning and data mining techniques have been effective in extracting textual data from news, blogs, and social media websites. The data of search engine trafficking are also utilized as inputs for training the model. The use of RNN as a predictive model is currently being replaced by LSTM, which solves the problem of exploding and vanishing gradients. Studies suggest an improvement in the model's performance by incorporating transfer learning with word embeddings.

From a financial viewpoint, it is necessary to evaluate the performance of models in terms of realized profits, returns or financial ratios rather than solely depending upon accuracy, RMSE, MAPE of the model implemented. Machine learning applications in portfolio management have surpassed the performance of benchmark models: 1/N or market index value, by yielding higher returns. Along with the usage of classical machine learning and DNN, this area has witnessed reinforcement learning for creating an agent trader to perform trading activities rationally like humans. This application has emerged during the last three years and its potential needs to be fully explored.

Owing to the uproar that digital currencies could be the latest era for settling transactions in the near future, there is a need to thoroughly understand and explore the crypto market. As the application of machine learning in cryptocurrency prediction is in its infancy, it is impossible to determine which model would be best suited for crypto forecasting. Prior literature lacks the use of high-frequency data that can capture financial time-series behaviour. The entire cryptocurrency market is still chaotic. Lack of market supervision may be the key factor for its relatively low efficiency. Also, the market may be more dominated by uninformed traders allowing informed traders to speculate.

The application of machine learning models in forex prediction has proved to be successful due to its ability to model non-linear time series. The study identifies EUR/USD as the prominent standard used for exchange rate prediction, while very few studies attempt to predict forex rates of other currencies. Published studies in this area are steadily increasing over the last three years, indicating an upcoming field worth further research.

Another area contributing to unsteadiness in the economy's financial sector is the currency crisis, sovereign defaults, and credit default swaps. However, the current study identifies a lack of supporting literature in this area to predict financial crises. The use of deep learning models such as CNN, RNN, LSTM, GRU, hybrid, and ensemble models is very limited in this area compared to classical machine models such as SVM, decision tree, and Random Forest. Since economic conditions are not static, financial crises prediction continues to be an open area of research.

The literature reviewed indicates increasing research in financial applications of machine learning since 2015. In recent years, continuous increasing interest is seen in stock markets to enhance predictive performance, while 2021 has witnessed a colossal spike in cryptocurrency studies marking the interest of researchers and academicians. Researchers from China have made significant contributions in financial applications of machine learning, followed by India and U.S.A.

The focus of our review was on the recent progress of machine learning and deep learning applications, without giving a whole picture of the relevant history. The scope of this study was limited only to six financial domains without discussing the application of machine learning and deep learning in other important financial domains. Since our study exclusively focused on journal papers published in ScienceDirect, there is a possibility to miss relevant articles published in other databases.

Each model carries its advantages and shortcomings depending upon the circumstances in which they are implemented. Training models with different features, testing on different financial datasets, and using different performance metrics, incapacitates us to compare models implemented in various studies.

Although sporadic instances of statistical models having comparable or even better results than machine learning, the general trend remains the reverse. Overall, machine learning models, including deep learning, hybrid models, and ensemble models, outperform traditional models in the field of finance. There is still much scope for implementing machine learning and its subsets in finance.

7. Lessons learned

The application of machine learning in stock markets is massive compared to other areas of finance. Analysing the results obtained from machine learning, deep learning, and hybridized models, LSTM shows remarkable performance in forecasting the future prices of stocks and indices. This model also showcases a high accuracy on binary data while classifying stocks' future up-ward and downward directions. The ability of the LSTM model to remember short-term and long-term data proves its superiority in predicting the financial time series. Future research should focus on training models with high-frequency data and predicting intraday stock prices. Machine learning and deep learning models can be applied to predict the volatility of stock markets in emerging economies and analyse the impacts of financial disclosures or financial announcements on stock markets. The application of Random Forest for portfolio management results in high returns in several studies, proving its reliability in this area. A rational investor can gain excessive returns while trading during the oscillating market period by applying predictive models. Future research in this area could focus on forming portfolios for developed and developing countries separately in order to compare the performance of Random Forest on the dynamics of different datasets. Research on online portfolio management is also encouraged.

In cryptocurrency prediction, the feature inputs utilized to train the models were similar to those used in stock market prediction, in addition to crypto market information such as hash rate, mempool transaction count, mempool size, and block size. Although LSTM has proved its ability to predict a noisy and chaotic time series for Bitcoin and Ethereum, the model's ability to predict the other cryptocurrencies remains untouched.

Various models are applied to predict forex rates, mainly USD/EUR and USD/GBP between North America and Europe and USD/JPY between North America and Asia. There lies considerable scope for researching the most accurate model for predicting exchange rates between a developed and developing economy. Also, Auto Weka software can be applied to datasets of different timestamps to check the accuracy of the model since its accuracy is the highest in the literature under review.

While the accuracy of predicting financial crises averages between 70 and 80 %, SVMs have shown a remarkable performance, particularly on U.S. datasets. In order to rely on this model for predicting an early warning signal, it's performance should be tested on datasets of other countries by measuring the contagion effect between them.

The training datasets are a significant issue faced in predicting bankruptcy, insolvency, or financial distress using machine learning. Some of the datasets used have an equal number of healthy and non-healthy firms (balanced datasets). In real-world situations, the number of unhealthy firms is significantly much less than healthy firms. SVM models are frequently used in this area due to their well-known and tested performance in 2-group classification. Additionally, the study identifies a lack of research on predicting bank insolvency. There is an increasing need for studies to develop models to avoid the spread of financial turbulence to the entire economy.

Emerging areas like cryptocurrency and blockchain studies are relatively new and need to be explored in order to determine the usefulness of machine learning techniques in these areas. Also, the surveys conducted on detecting financial crisis using machine learning were very few in recent years. Such topics were thoroughly examined and many articles published right after a crisis occurred. Likewise, its applications in portfolio management are also limited in relevance with the period under study. Another area to be considered is the use of machine learning in detecting anomalies in financial statements.

We find that classical machine learning models such as decision tree, Random Forest, SVM, k-NN, and Bayesian models are still in use, despite many deep learning models taking the lead due to their complex architecture and ability to mimic the human brain. LSTM and GRU, having roots from RNN models, are being widely explored in time-series data due to their long-term dependencies, while CNN models have demonstrated the best performance using input images for training. The use of ensemble models in finance is still a work-in-progress; nevertheless, based on the few models implemented in the existing reviewed literature, their predictive performance outperforms that of its constituent models individually. This is another area in need of research and examination.

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CRediT authorship contribution statement

Noella Nazareth: Data curation, Formal analysis, Methodology, Visualization, Writing - original draft. **Yeruva Venkata Ramana Reddy:** Conceptualization, Supervision, Writing - review & editing

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

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References

Adegboye, A., & Kampouridis, M. (2021). Machine learning classification and regression models for predicting directional changes trend reversal in FX markets. *Expert Systems With Applications, 173*(114645), 1–15. https://doi.org/10.1016/j.eswa.2021.114645. Retrieved from.

Aguilar-Rivera, R., Valenzuela-Rendón, M.-R., & Rodríguez-Ortiz, J. (2015). Genetic algorithms and Darwinian approaches in financial applications: A survey. *Expert Systems with Applications, 42*(21), 7684–7697. https://doi.org/10.1016/j.eswa.2015.06.001. Retrieved from.

Ahmed, S., Hassan, S.-U., Aljohani, N. R., & Nawaz, R. (2020). FLF-LSTM: A novel prediction system using Forex Loss Function. *Applied Soft Computing Journal, 97*, Article 106780. https://doi.org/10.1016/j.asoc.2020.106780. Retrieved from.

Akhtar, M. M., Zamani, A. S., Khan, S., Shatat, A. S., & Dilshad, S. (2022). Stock market prediction based on statistical data using machine learning algorithms. *Journal of King Saud University – Science, 34*(101940), 1–7. https://doi.org/10.1016/j.jksus.2022.101940. Retrieved from.

Alessi, L., & Detken, C. (2018). Identifying excessive credit growth and leverage. *Journal of Financial Stability, 35*, 215–225. https://doi.org/10.1016/j.jfs.2017.06.005. Retrieved from.

Alexandre, R. (2022). Machine learning portfolios with equal risk contributions: Evidence from the Brazilian market. *Emerging Markets Review, 51*(100891), 1–31. https://doi.org/10.1016/j.ememar.2022.100891. Retrieved from.

Alonso-Monsalve, S., Suárez-Cetrulo, A. L., Cervantes, A., & Quintana, D. (2020). Convolution on neural networks for high-frequency trend prediction of cryptocurrency exchange rates using technical indicators. *Expert Systems With Applications, 149*, Article 113250. https://doi.org/10.1016/j.eswa.2020.113250. Retrieved from.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Retrieved from *The Journal of Finance, 23*(4), 589–609 https://www.jstor.org/stable/2978933.

Ardabili, S., Abdolalizadeh, L., Mako, C., Torok, B., & Mosavi, A. (2022). Systematic review of deep learning and machine learning for building energy. *Frontiers in Energy Research, 10*, 1–19. https://doi.org/10.3389/fenrg.2022.786027

Atkins, A., Niranjan, M., & Gerding, E. (2018). Financial news predicts stock market volatility better than close price. *The Journal of Finance and Data Science, 4*, 120–137. https://doi.org/10.1016/j.jfds.2018.02.002

Ayala, J., Garcia-Torres, M., Noguera, J. L., Gomez-Vela, F., & Divina, F. (2021). Technical analysis strategy optimization using a machine learning approach in stock market indices. *Knowledge-Based Systems, 225*. https://doi.org/10.1016/j.knosys.2021.107119

Babecký, J., Havránek, T., Matějů, J., Rusnák, M., Šmídková, K., & Vašíček, B. (2014). Banking, debt, and currency crises in developed countries: Stylized facts and early warning indicators. *Journal of Financial Stability, 15*, 1–17. https://doi.org/10.1016/j.jfs.2014.07.001. Retrieved from.

Baek, S., Mohanty, S. A., & Glambosky, M. (2020). COVID-19 and stock market volatility: An industry level analysis. *Finance Research Letters, 37*. https://doi.org/10.1016/j.frl.2 020.101748

Bahrammirzaee, A. (2010). A comparative survey of artificial intelligence applications in finance: Artificial neural networks, expert system and hybrid intelligent systems.

Neural Computing and Applications, 19(8), 1165–1195. https://doi.org/10.1007/s00521-010-0362-z

Banik, S., Sharma, N., Mangla, M., Mohanty, S. N., & Shitharth, S. (2022). LSTM based decision support system for swing trading in stock market. *Knowledge-Based Systems, 239*(107994), 1–8. https://doi.org/10.1016/j.knosys.2021.107994. Retrieved from.

Barboza, F., Kimura, H., & Altman, E. (2017). Machine learning models and bankruptcy prediction. *Expert Systems with Applications, 83*, 405–417. https://doi.org/10.1016/j.eswa.2017.04.006. Retrieved from.

Barua, R., & Sharma, A. K. (2022). Dynamic Black Litterman portfolios with views derived via CNN-BiLSTM predictions. *Financce Research Letters, 49*(103111), 1–7. https://doi.org/10.1016/j.frl.2022.103111. Retrieved from.

Basak, S., Kar, S., Saha, S., Khaidem, L., & Dey, S. R. (2019). Predicting the direction of stock market prices using tree-based classifiers. *North American Journal of Economics, 47*, 552–567. https://doi.org/10.1016/j.najef.2018.06.013

Basher, S. A., & Sadorsky, P. (2022). Forecasting Bitcoin price direction with random forests: How important are interest rates, inflation, and market volatility? *Machine Learning with Applications*. https://doi.org/10.1016/j.mlwa.2022.10035. ***100355***, 1–19. Retrieved from.

Beaver, W. H. (1966). Financial ratios as predictors of failure. Retrieved from *Journal of Accounting Research, 4*(1996), 71–111 http://www.jstor.org/stable/2490171.

Betancourt, C., & Chen, W.-H. (2021). Deep reinforcement learning for portfolio management of markets with a dynamic number of assets. *Expert Systems with Applications, 164*(114002), 1–10. https://doi.org/10.1016/j.eswa.2020.114002. Retrieved from.

Beutel, J., List, S., & Schweinitz, G. (2019). Does machine learning help us predict banking crises? *Journal of Financial Stability, 45*(100693). https://doi.org/10.1016/j.jfs.2019.100693. Retrieved from.

Bhandari, H. N., Rimal, B., Pokhrel, N. R., Rimal, R., Dahal, K. R., & Khatri, R. K. (2022). Predicting stock market index using LSTM. *Machine Learning with Applications, 9* (100320), 1–15. https://doi.org/10.1016/j.mlwa.2022.100320. Retrieved from.

Bustos, O., & Quimbaya, P. A. (2020). Stock market movement forecast: A Systematic review. *Expert Systems with Applications, 156*. https://doi.org/10.1016/j.eswa.2020.113464

Cambria, E. (2016). Affective computing and sentiment analysis. *IEEE Xplore, 31*(2), 102–107. https://doi.org/10.1109/MIS.2016.31

Cao, L. (2020). AI in finance: A review. *SSRN Electronic Journal, 00*, 1–47. https://doi.org/10.2139/ssrn.3647625

Cavalcante, R. C., Brasileiro, R. C., Souza, V. L., Nobrega, J. P., & Oliveira, A. L. (2016). Computational intelligence and financial markets: A survey and future directions. *Expert Systems with Applications, 55*, 194–211. https://doi.org/10.1016/j.eswa.2016.02.006. Retrieved from.

Chandra, R., & Chand, S. (2016). Evaluation of co-evolutionary neural network architectures for time series prediction with mobile application in finance. *Applied Soft Computing, 49*, 462–473. https://doi.org/10.1016/j.asoc.2016.08.029

Chandrinos, S. K., Sakkas, G., & Lagaros, N. D. (2018). AIRMS: A risk management tool using machine learning. *Expert Systems with Applications, 105*, 34–48. https://doi.org/10.1016/j.eswa.2018.03.044. Retrieved from.

Chatzis, S. P., Siakoulis, V., Petropoulos, A., Stavroulakis, E., & Vlachogiannakis, N. (2018). Forecasting stock market crisis events using deep and statistical machine learning techniques. *Expert Systems With Applications, 112*, 353–371. https://doi.org/10.1016/j.eswa.2018.06.032. Retrieved from.

Chen, Y., & Hao, Y. (2017). A feature weighted support vector machine and K-nearest neighbor algorithm for stock market indices prediction. *Expert Systems with Applications, 80*, 340–355. https://doi.org/10.1016/j.eswa.2017.02.044

Chen, Z., Li, C., & Sun, W. (2020). Bitcoin price prediction using machine learning: An approach to sample dimension engineering. *Journal of Computational and Applied Mathematics, 365*, Article 112395. https://doi.org/10.1016/j.cam.2019.112395. Retrieved from.

Chen, W., Zhang, H., Mehlawat, M. K., & Jia, L. (2021). Mean–variance portfolio optimization using machine learning-based stock price prediction. *Applied Soft Computing Journal, 100*, Article 106943. https://doi.org/10.1016/j.asoc.2020.106943. Retrieved from.

Chong, E., Han, C., & Park, F. C. (2017). Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. *Expert Systems with Applications, 83*, 187–205. https://doi.org/10.1016/j.eswa.2017.04.030

Chowdhury, R., Rahman, A. M., Rahman, S. M., & Mahdy, M. (2020). An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning. *Physica A, 551*, Article 124569. https://doi.org/10.1016/j.physa.2020.124569. Retrieved from.

Dabrowski, J. J., Beyers, C., & Pieter de Villiers, J. (2016). Systemic banking crisis early warning systems using dynamic Bayesian networks. *Expert Systems with Applications, 62*, 225–242. https://doi.org/10.1016/j.eswa.2016.06.024. Retrieved from.

Das, S., Behera, R. K., Kumar, M., & Rath, S. K. (2018). Real-Time Sentiment Analysis of Twitter Streaming data for Stock Prediction. *International Conference on Computational Intelligence and Data Science (ICCIDS 2018)*, *132*, pp. 956-964. http://10.1016/j.procs.2018.05.111.

Dawood, M., Horsewood, N., & Strobel, F. (2017). Predicting sovereign debt crises: An early warning system approach. *Journal of Financial Stability, 28*, 16–28. https://doi.org/10.1016/j.jfs.2016.11.008

Duca, M. L., Koban, A., Basten, M., Bengtsson, E., Klaus, B., Kusmierczyk, P., . . . Peltonen, T. (2017). *A New Database for Financial Crises in European Countries–ECB/ESRB EU Crises Database.* Technical Report, ECB Ocassional Paper.

Eachempati, P., Srivastava, P. R., Kumar, A., Tan, K. H., & Gupta, S. (2021). Validating the impact of accounting disclosures on stock market: A deep neural network approach. *Technological Forecasting & Social Change, 170*(120903), 1–14. https://doi.org/10.1016/j.techfore.2021.120903. Retrieved from.

Emerson, S., Kennedy, R., O'Shea, L., & O'Brien, J. (2019). Trends and Applications of Machine Learning in Quantative Finance. *8th International Conference on Economics and Finance Research (ICEFR)*. Retrieved from https://ssrn.com/abstract=3397005.

Fadlalla, A., & Lin, C.-H. (2001). An analysis of the applications of neural networks in finance. *Interfaces, 31*(4), 112–122. https://doi.org/10.1287/inte.31.4.112.9662

Fama, E. (1965). The behaviour of stock market prices. *The Journal of Business, 38*, 34–105. http://www.jstor.org/stable/2350752.

Farimani, S. A., Jahan, M. V., Fard, A. M., & Tabbakh, S. R. (2022). Investigating the informativeness of technical indicators and news sentiment in financial market price prediction. *Knowledge-Based Systems, 247*(108742), 1–11. https://doi.org/10.1016/j.knosys.2022.108742. Retrieved from.

Galeshchuk, S. (2016). Neural networks performance in exchange rate prediction. *Neurocomputing, 172*, 446–452. https://doi.org/10.1016/j.neucom.2015.03.100. Retrieved from.

Garcia, J. (2022). Bankruptcy prediction using synthetic sampling. *Machine Learning with Applications, 9*(100343), 1–11. https://doi.org/10.1016/j.mlwa.2022.100343. Retrieved from.

Gerlein, E. A., McGinnity, M., Belatreche, A., & Coleman, S. (2016). Evaluating machine learning classification for financial trading: An empirical approach. *Expert Systems with Applications, 54*, 193–207. https://doi.org/10.1016/j.eswa.2016.01.018. Retrieved from.

Gogas, P., Papadimitriou, T., & Agrapetidou, A. (2018). Forecasting bank failures and stress testing: A machine learning approach. *International Journal of Forecasting, 34* (3), 440–455. https://doi.org/10.1016/j.ijforecast.2018.01.009. Retrieved from.

Gupta, U., Bhattacharjee, V., & Bishnu, P. S. (2022). StockNet—GRU based stock index prediction. *Expert Systems with Applications, 207*(117986), 1–16. https://doi.org/10.1016/j.eswa.2022.117986. Retrieved from.

Hassanniakalager, A., Sermpinis, G., & Stasinakis, C. (2021). Trading the foreign exchange market with technical analysis and Bayesian Statistics. *Journal of Empirical Finance, 63*, 230–251. https://doi.org/10.1016/j.jempfin.2021.07.006. Retrieved from.

Hawley, D. D., Johnson, J. D., & Raina, D. (1990). Artificial neural systems: A new tool for financial decision-making. *Financial Analysts Journal, 46*(6), 63–72. https://doi.org/10.2469/faj.v46.n6.63

Heston, S., & Sinha, N. R. (2018). News vs. Sentiment: Predicting stock returns from news stories. *Financial Analysts Journal, 73*(3), 67–83. https://doi.org/10.2469/faj.v73.n3.3. Retrieved from.

Hiransha, M., Gopalakrishnan, E. A., Vijay Krishna, M., & Soman, K. P. (2018). NSE stock market prediction using deep-learning models. *International Conference on Computational Intelligence and Data Science (ICCIDS 2018), 132*, 1351–1362. https://doi.org/10.1016/j.procs.2018.05.050

Hosaka, T. (2019). Bankruptcy prediction using imaged financial ratios and convolutional neural networks. *Expert Systems with Applications*, 287–299. https://doi.org/10.1016/j.eswa.2018.09.039

Huang, J., Chai, J., & Cho, S. (2020). Deep learning in finance and banking: A literature review and classification. *Frontiers of Business Research in China, 14*(1). https://doi.org/10.1186/s11782-020-00082-6

Ibrahim, A., Kashef, R., & Corrigan, L. (2021). Predicting market movement direction for bitcoin: A comparison of time series modeling methods. *Computers and Electrical Engineering, 89*, 106905. https://doi.org/10.1016/j.compeleceng.2020.106905, 1-10.

Islam, M., & Hossain, E. (2020). Foreign exchange currency rate prediction using a GRU-LSTM hybrid network. *Soft Computing Letters*. https://doi.org/10.1016/j.socl.2020.100009

Jabeur, S. B., Gharib, C., Mefteh-Wali, S., & Arfi, W. B. (2021). CatBoost model and artificial intelligence techniques for corporate failure prediction. *Technological Forecasting & Social Change, 16*, 120658. https://doi.org/10.1016/j.techfore.2021.120658, 1-19.

Jaquart, P., Dann, D., & Weinhardt, C. (2021). Short-term bitcoin market prediction via machine learning. *The Journal of Finance and Data Science, 7*, 45–66. https://doi.org/10.1016/j.jfds.2021.03.001

Jardin, P. D. (2021). Dynamic self-organizing feature map-based models applied to bankruptcy prediction. *Decision Support Systems, 147*, 113576. https://doi.org/10.1016/j.dss.2021.113576, 1-15.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2017). Macrofinancial history and the new business cycle facts. *NBER Macroeconomics Annual, 31*, 213–263.

Juan, D. (2022). Mean–variance portfolio optimization with deep learning based-forecasts for cointegrated stocks. *Expert Systems with Applications, 201*, 117005, 1-11.

Keyan, L., Jianan, Z., & Dayong, D. (2021). Improving stock price prediction using the long short-term memory model combined with online social networks. *Journal of Behavioral and Experimental Finance, 30*. https://doi.org/10.1016/j.jbef.2021.100507

Khattak, M. A., Ali, M., & Rizvi, S. A. (2021). Predicting the European stock market during COVID-19: A machine learning approach. *MethodsX, 8*. https://doi.org/10.1016/j.mex.2020.101198

Kia, A. N., Haratizadeh, S., & Shouraki, S. B. (2018). A hybrid supervised semi-supervised graph-based model to predict one-day ahead movement of global stock markets and commodity prices. *Expert Systems With Applications, 105*, 159–173. https://doi.org/10.1016/j.eswa.2018.03.037

Kim, H.-M., Bock, G.-W., & Lee, G. (2021). Predicting Ethereum prices with machine learning based on Blockchain information. *Expert Systems with Applications, 184*, 115480. https://doi.org/10.1016/j.eswa.2021.115480, 1-8.

Kinyua, J. D., Mutigwe, C., Cushing, D. J., & Poggi, M. (2021). An analysis of the impact of President Trump's tweets on the DJIA and S&P 500 using machine learning and sentiment analysis. *Journal of Behavioral and Experimental Finance, 29*. https://doi.org/10.1016/j.jbef.2020.100447

Koratamaddi, P., Wadhwani, K., Gupta, M., & Sanjeevi, S. G. (2021). Market sentiment-aware deep reinforcement learning approach for stock portfolio allocation. *Engineering Science and Technology, an International Journal, 24*(4), 848–859. https://doi.org/10.1016/j.jestch.2021.01.007

Koyuncugil, A. S., & Ozgulbas, N. (2012). Financial early warning system model anddata mining application for risk detection. *Expert Systems with Applications, 39*(6), 6238–6253. https://doi.org/10.1016/j.eswa.2011.12.021

Kraus, M., & Feuerriegel, S. (2017). Decision support from financial disclosures with deep neural networks and transfer learning. *Decision Support Systems, 104*, 38–48. https://doi.org/10.1016/j.dss.2017.10.001

Kumbure, M. M., Lohrmann, C., Luukka, P., & Porras, J. (2022). Machine learning techniques and data for stock market forecasting: A literature review. *Expert Systems with Applications, 197*, 116659. https://doi.org/10.1016/j.eswa.2022.116659, 1-41.

Kwak, Y., Song, J., & Lee, H. (2021). Neural network with fixed noise for index-tracking portfolio optimization. *Expert Systems with Applications, 183*, 115298. https://doi.org/10.1016/j.eswa.2021.115298, 1-11.

Laborda, R., & Olmo, J. (2021). Volatility spillover between economic sectors in financial crisis prediction: Evidence spanning the great financial crisis and Covid-19 pandemic. *Research in International Business and Finance, 57*(November 2020), 101402. https://doi.org/10.1016/j.ribaf.2021.101402

Lahmiri, S., & Bekiros, S. (2020). Intelligent forecasting with machine learning trading systems in chaotic intraday Bitcoin market. *Chaos, Solitons and Fractals Nonlinear Science, and Nonequilibrium and Complex Phenomena, 133*, Article 109641. https://doi.org/10.1016/j.chaos.2020.109641. Retrieved from.

Lainà, P., Nyholm, J., & Sarlin, P. (2015). Leading indicators of systemic banking crises: Finland in a panel of EU countries. *Review of Financial Economics, 24*, 18–35. https://doi.org/10.1016/j.rfe.2014.12.002

Li, Y., Bu, H., Li, J., & Wu, J. (2020). The role of text-extracted investor sentiment in Chinese stock price prediction with the enhancement of deep learning. *International Journal of Forecasting, 36*, 1541–1562. https://doi.org/10.1016/j.ijforecast.2020.05.001

Liang, D., Lu, C.-C., Tsai, C.-F., & Shih, G.-A. (2016). Financial ratios and corporate governance indicators in bankruptcy prediction: A comprehensive study. *European Journal of Operational Research, 252*(2), 561–572. https://doi.org/10.1016/j.ejor.2016.01.012

Lim, H. W., Jeong, S. H., Oh, K. J., & Lee, H. S. (2022). Neural network foreign exchange trading system using CCS-IRS basis: Empirical evidence from Korea. *Expert Systems With Applications, 205*, 117718. https://doi.org/10.1016/j.eswa.2022.117718, 1-11. Retrieved from.

Lin, C.-S., Khan, H., Chang, R.-Y., & Wang, Y.-C. (2008). A new approach to modeling early warning systems for currency crises: Can a machine-learning fuzzy expert system predict the currency crises effectively? *Journal of International Money and Finance, 27*, 1098–1121. https://doi.org/10.1016/j.jimonfin.2008.05.006

Liu, M., Li, G., Li, J., Zhu, X., & Yao, Y. (2021). Forecasting the price of Bitcoin using deep learning. *Finance Research letters, 40*, Article 101755. https://doi.org/10.1016/j.frl.2020.101755. Retrieved from.

Lohrmann, C., & Luukka, P. (2019). Classification of intraday S&P500 returns with a Random Forest. *International Journal of Forecasting, 35*, 390–407. https://doi.org/10.1016/j.ijforecast.2018.08.004

Long, J., Chen, Z., He, W., Wu, T., & Ren, J. (2020). An integrated framework of deep learning and knowledge graph for prediction of stock price trend: An application in Chinese stock exchange market. *Applied Soft Computing Journal, 91*. https://doi.org/10.1016/j.asoc.2020.106205

Ma, Y., Han, R., & Wang, W. (2021). Portfolio optimization with return prediction using deep learning and machine learning. *Expert Systems with Applications, 165*(June 2020), 113973. https://doi.org/10.1016/j.eswa.2020.113973

Ma, C., & Yan, S. (2022). Deep learning in the Chinese stock market: The role of technical indicators. *Finance Research Letters, 49*, 103025. https://doi.org/10.1016/j.frl.2022.103025, 1-9.

Mai, F., Tian, S., Lee, C., & Ma, L. (2019). Deep learning models for bankruptcy prediction using textual disclosures. *European Journal of Operational Research, 274* (2), 743–758. https://doi.org/10.1016/j.ejor.2018.10.024

Malagrino, L. S., Roman, N. T., & Monteiro, A. M. (2018). Forecasting stock market index daily direction: A Bayesian Network approach. *Expert Systems With Applications, 105*, 11–22. https://doi.org/10.1016/j.eswa.2018.03.039

Malandri, L., Xing, F. Z., Orsenigo, C., Vercellis, C., & Cambria, E. (2018). Public mood-driven asset allocation: The importance of financialsentiment in portfolio management. *Cognitive Computation, 10*, 1167–1176. https://doi.org/10.1007/s12559-018-9609-2. Retrieved from.

Mallqui, D. C., & Fernandes, R. A. (2019). Predicting the direction, maximum, minimum and closing prices of daily Bitcoin exchange rate using machine learning techniques. *Applied Soft Computing Journal, 75*, 596–606. https://doi.org/10.1016/j.asoc.2018.11.038. Retrieved from.

Manthoulis, G., Doumpos, M., Zopounidis, C., & Galariotis, E. (2020). An ordinal classification framework for bank failure prediction: Methodology and empirical evidence for US banks. *European Journal of Operational Research, 282*(2), 786–801. https://doi.org/10.1016/j.ejor.2019.09.040. Retrieved from.

Maqsood, H., Mehmood, I., Maqsood, M., Yasir, M., Afzal, S., Aadil, F., & Muhammad, K. (2020). A local and global event sentiment based efficient stock exchange forecasting using deep learning. *International Journal of Information Management, 50*, 432–451. https://doi.org/10.1016/j.ijinfomgt.2019.07.011

Markowitz, H. (1952). Portfolio selection. Retrieved from *The Journal of Finance, 7*(1), 77–91 https://www.jstor.org/stable/2975974.

Matin, R., Hansen, C., Hansen, C., & Mølgaard, P. (2019). Predicting distresses using deep learning of text segments in annual reports. *Expert Systems with Applications, 132*, 199–208. https://doi.org/10.1016/j.eswa.2019.04.071

Milhomem, D. A., & Dantas, M. J. (2020). Analysis of new approaches used in portfolio optimization: A systematic literature review. *Production, 30*(1), 1–16. https://doi.org/10.1590/0103-6513.20190144

Moghaddam, A. H., & Momtazi, S. (2021). Image processing meets time series analysis: Predicting Forex profitable technical pattern positions. *Applied Soft Computing, 108*, Article 107460. https://doi.org/10.1016/j.asoc.2021.107460. Retrieved from.

Mohiuddin, R. A. (2021). LSTM-based deep learning model for stock prediction and predictive optimization model. *EURO Journal on Decision Processes, 9*, 100001. https://doi.org/10.1016/j.ejdp.2021.100001, 1-11.

Mselmi, N., Lahiani, A., & Hamza, T. (2017). Financial distress prediction: The case of French small and medium-sized firms. *International Review of Financial Analysis, 50*, 67–80. https://doi.org/10.1016/j.irfa.2017.02.004

Nabipour, M., Nayyyeri, P., Jabani, H., Shahab, S., & Mosavi, A. (2020). Predicting stock market trends using machinelearning and deep learning algorithms via continuous and binary data;a comparative analysis. *IEEE Access, 8*, 150199–150212. https://doi.org/10.1109/ACCESS.2020.3015966

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. Retrieved from www.bitcoin.org.

Nasirtafreshi, I. (2022). Forecasting cryptocurrency prices using Recurrent Neural Network and Long Short-term Memory. *Data & Knowledge Engineering, 139*, 102009. https://doi.org/10.1016/j.datak.2022.102009, 1-12. Retrieved from.

Nosratabadi, S., Mosavi, A., Duan, P., Ghamisi, P., Filip, F., Band, S. S., & Gandomi, A. H. (2020). Data science in economics: comprehensive review of advanced machine learning and deep learning methods. *Mathematics, 8*(10), 1–25. https://doi.org/10.3390/math8101799

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. Retrieved from *Journal of Accounting Research, 18*(1), 109–131 https://www.jstor.org/stable/2490395.

Ortu, M., Uras, N., Conversano, C., Bartolucci, S., & Destefanis, G. (2022). On technical trading and social media indicators for cryptocurrency price classification through deep learning. *Expert Systems With Applications, 198*, 116804. https://doi.org/10.1016/j.eswa.2022.116804, 1-15. Retrieved from.

Ouyang, Z.-S., Yang, X.-T., & Lai, Y. (2021). Systemic financial risk early warning of financial market in China using Attention-LSTM model. *North American Journal of Economics and Finance, 56*(January), 1–16. https://doi.org/10.1016/j.najef.2021.101383. Retrieved from.

Ozbayoglu, A. M., Gudelek, M. U., & Sezer, O. B. (2020). Deep learning for financial applications: A survey. *Applied Soft Computing Journal, 93*, Article 106384. https://doi.org/10.1016/j.asoc.2020.106384. Retrieved from.

Paiva, F. D., Cardoso, R. T., Hanaoka, G. P., & Duarte, W. M. (2019). Decision-making for financial trading: A fusion approach of machine learning and portfolio selection. *Expert Systems with Applications, 115*, 635–655. https://doi.org/10.1016/j.eswa.2018.08.003. Retrieved from.

Park, H. J., Kim, Y., & Kim, H. Y. (2022). Stock market forecasting using a multi-task approach integrating long short-term memory and the random forest framework. *Applied Soft Computing, 114*(108106), 1–17. https://doi.org/10.1016/j.asoc.2021.108106. Retrieved from.

Patel, M. M., Tanwar, S., Gupta, R., & Kumar, N. (2020). A deep learning-based cryptocurrency price prediction scheme for financial institutions. *Journal of Information Security and Applications, 55*, Article 102583. https://doi.org/10.1016/j.jisa.2020.102583. Retrieved from.

Peng, Y., Albuquerque, P. H., Camboim de Sa, J. M., Padula, A. J., & Montenegro, M. R. (2018). The best of two worlds: Forecasting high frequency volatility for cryptocurrencies and traditional currencies with Support Vector Regression. *Expert Systems with Applications, 97*, 177–192. https://doi.org/10.1016/j.eswa.2017.12.004

Peng, Y., Albuquerque, P. H., Kimura, H., & Saavedra, C. A. (2021). Feature selection and deep neural networks for stock price direction forecasting using technical analysis indicators. *Machine Learning with Applications, 5*, 100060. https://doi.org/10.1016/j.mlwa.2021.100060, 1-39. Retrieved from.

Peng, Y.-L., & Lee, W.-P. (2021). Data selection to avoid overfitting for foreign exchange intraday trading with machine learning. *Applied Soft Computing, 108*, Article 107461. https://doi.org/10.1016/j.asoc.2021.107461. Retrieved from.

Petropoulos, A., & Siakoulis, V. (2021). Can central bank speeches predict financial market turbulence? Evidence from an adaptive NLP sentiment index analysis using XGBoost machine learning technique. *Central Bank Review, 21*, 141–153. https://doi.org/10.1016/j.cbrev.2021.12.002. Retrieved from.

Petropoulos, A., Siakoulis, V., Stavroulakis, E., & Vlachogiannakis, N. E. (2020). Predicting bank insolvencies using machine learning techniques. *International Journal of Forecasting, 36*(3), 1092–1113. https://doi.org/10.1016/j.ijforecast.2019.11.005. Retrieved from.

Picasso, A., Merello, S., Ma, Y., Oneto, L., & Cambria, E. (2019). Technical analysis and sentiment embeddings for market trend prediction. *Expert Systems with Applications, 135*, 60–70. https://doi.org/10.1016/j.eswa.2019.06.014. Retrieved from.

Pinelis, M., & Ruppert, D. (2022). Machine learning portfolio allocation. *The Journal of Finance and Data Science, 8*, 35–54. https://doi.org/10.1016/j.jfds.2021.12.001. Retrieved from.

Plessis, E.d. (2022). Multinomial modeling methods: Predicting four decades of international banking crises. *Economic Systems, 46*, 100979. https://doi.org/10.1016/j.ecosys.2022.100979, 1-34. Retrieved from.

Pokhrel, N. R., Dahal, K. R., Rimal, R., Bhandari, H. N., Khatri, R. K., Rimal, B., & Hahn, W. E. (2022). Predicting NEPSE index price using deep learning models. *Machine Learning With Applications*, 1–39. https://doi.org/10.1016/j.mlwa.2022.100385. Retrieved from.

Poongodi, M., Sharma, A., Vijayakumar, V., Bhardwaj, V., Sharma, A. P., Iqbal, R., & Kumar, R. (2020). Prediction of the price of Ethereum blockchain cryptocurrency in an industrial finance system. *Computers and Electrical Engineering, 81*, Article 106527. https://doi.org/10.1016/j.compeleceng.2019.106527. Retrieved from.

Pulakkazhy, S., & Balan, R. (2013). Data mining in banking and its applications- A review. *Journal of Computer Science, 9*(10), 1252–1259. https://doi.org/10.3844/jcssp.2013.1252.1259

Qiu, M., Song, Y., & Akagi, F. (2016). Application of artificial neural network for the prediction of stock market returns: The case of the Japanese stock market. *Chaos, Solitons and Fractals, 85*, 1–7. https://doi.org/10.1016/j.chaos.2016.01.004

Rathore, R. K., Mishra, D., Mehra, P. S., Pal, O., Hashim, A. S., Shapi'i, A., & Shutaywi, M. (2022). Real-world model for bitcoin price prediction. *Information Processing and Management, 59*, 102968. https://doi.org/10.1016/j.ipm.2022.102968, 1-21. Retrieved from.

Riyazahmed, K. (2021). Neural networks in finance: A descriptive systematic review. *Indian Journal of Finance and Banking, 5*(2), 1–27. https://doi.org/10.46281/ijfb.v5i2.997

Rundo, F., Trenta, F., & di Stallo, A. L. (2019). Machine learning for quantitative finance applications: A survey. *Applied Sciences (Switzerland), 9*(24), 1–20. https://doi.org/10.3390/app9245574

Samitasa, A., Kampourisb, E., & Kenourgios, D. (2020). Machine learning as an early warning system to predict financial crisis. *International Review of Financial Analysis, 71*(November 2019). https://doi.org/10.1016/j.irfa.2020.101507

Saud, A. S., & Shakya, S. (2020). Analysis of look back period for stock price prediction with RNN variants: A case study on banking sector of NEPSE. *International Conference on Computational Intelligence and Data Science (ICCIDS 2019)*, *167*, pp. 788-798. http://10.1016/j.procs.2020.03.419.

Saurabh, S., & Dey, K. (2020). Unraveling the relationship between social moods and the stock. *Journal of Behavioral and Experimental Finance, 26*. https://doi.org/10.1016/j.jbef.2020.100300

Semiromi, H. N., Lessmann, S., & Peters, W. (2020). News will tell: Forecasting foreign exchange rates based on news story events in the economy calendar. *North American Journal of Economics and Finance, 52*(December 2018), Article 101181. https://doi.org/10.1016/j.najef.2020.101181. Retrieved from.

Seong, N., & Nam, K. (2022). Forecasting price movements of global financial indexes using complex quantitative financial networks. *Knowledge-Based Systems, 235*, 1–14. https://doi.org/10.1016/j.knosys.2021.107608. Retrieved from.

Shen, F., Chao, J., & Zhao, J. (2015). Forecasting exchange rate using deep belief networks and conjugate gradient method. *Neurocomputing, 167*, 243–253. https://doi.org/10.1016/j.neucom.2015.04.071. Retrieved from.

Son, H., Hyun, C., Phan, D., & Hwang, H. (2019). Data analytic approach for bankruptcy prediction. *Expert Systems with Applications, 138*, Article 112816. https://doi.org/10.1016/j.eswa.2019.07.033. Retrieved from.

Sun, J., Xiao, K., Liu, C., Zhou, W., & Xiong, H. (2019). Exploiting intra-day patterns for market shock prediction: A machine learning approach. *Expert Systems with Applications, 127*, 272–281. https://doi.org/10.1016/j.eswa.2019.03.006

Tan, Z., Yan, Z., & Zhu, G. (2019). Stock selection with random forest: An exploitation of excess return in the Chinese stock market. *Heliyon, 5*(8), e02310. Retrieved from.

Tkác, M., & Verner, R. (2016). Artificial neural networks in business: Two decades of research. *Applied Soft Computing, 38*, 788–804. https://doi.org/10.1016/j.asoc.2015.09.040. Retrieved from.

Tölö, E. (2020). Predicting systemic financial crises with recurrent neural networks. *Journal of Financial Stability, 49*, Article 100746. https://doi.org/10.1016/j.jfs.2020.100746. Retrieved from.

Veganzones, D., & Séverin, E. (2018). An investigation of bankruptcy prediction in imbalanced datasets. *Decision Support Systems, 112*, 111–124. https://doi.org/10.1016/j.dss.2018.06.011. Retrieved from.

Vellido, A., Lisboa, P., & Vaughan, J. (1999). Neural networks in business: A survey of applications (1992–1998). *Expert Systems with Applications, 17*(1), 51–70. Retrieved from 10.1016/s0957-4174(99)00016–0.

Vo, N. N., He, X., Liu, S., & Xu, G. (2019). Deep learning for decision making and the optimization of socially responsible investments and portfolio. *Decision Support Systems, 124*(July), Article 113097. https://doi.org/10.1016/j.dss.2019.113097. Retrieved from.

Wang, W., Li, W., Zhang, N., & Liu, K. (2020). Portfolio formation with preselection using deep learning from long-term financial data. *Expert Systems With Applications, 143*, Article 113042. https://doi.org/10.1016/j.eswa.2019.113042. Retrieved from.

Wang, C., Shen, D., & Li, Y. (2022). Aggregate investor attention and bitcoin return: The long short-term memory networks perspective. *Finance Research Letters, 49*, 103143. https://doi.org/10.1016/j.frl.2022.103143, 1-9. Retrieved from.

Wang, Y., Wang, C., Sensoy, A., Yao, S., & Cheng, F. (2022). Can investors' informed trading predict cryptocurrency returns? Evidence from machine learning. *Research in International Business and Finance, 62*, 101683. https://doi.org/10.1016/j.ribaf.2022.101683, 1-22. Retrieved from.

Weng, B., Ahmed, M. A., & Megahed, F. M. (2017). Stock market one-day ahead movement prediction using disparate data sources. *Expert Systems With Applications, 79*, 153–163. https://doi.org/10.1016/j.eswa.2017.02.041

Wong, B., Bodnovich, T. A., & Selvi, Y. (1997). Neural network applications in business: A review and analysis of the literature (1988–95). *Decision Support Systems, 19*(4), 301–320. https://doi.org/10.1016/s0167-9236(96)00070-x

Wong, B., & Selvi, Y. (1998). Neural network applications in finance: A review and analysis of literature (1990–1996). *Information & Management, 34*(3), 129–139. https://doi.org/10.1016/S0378-7206(98)00050-0

Wu, D., Ma, X., & Olson, D. L. (2022). Financial distress prediction using integrated Z-score and multilayer perceptron neural networks. *Decision Support Systems, 159*, 113814. https://doi.org/10.1016/j.dss.2022.113814, 1-8. Retrieved from.

Xing, Z. F., Cambria, E., & Zhang, Y. (2019). Sentiment-aware volatility forecasting. *Knowledge-Based Systems, 176*, 68–76. https://doi.org/10.1016/j.knosys.2019.03.029. Retrieved from.

Xing, F. Z., Cambria, E., & Welsch, R. E. (2018). *Intelligent Asset Allocation via Market Sentiment Views.* doi:10.1109/MCI.2018.2866727.

Zaremba, A., Kizys, R., Tzouvanas, P., Aharon, D. Y., & Demir, E. (2021). The quest for multidimensional financial immunity to the COVID-19 pandemic: Evidence from international stock markets. *Journal of International Financial Markets, Institutions & Money, 71*. https://doi.org/10.1016/j.intfin.2021.101284

Zhang, Y., Chu, G., & Shen, D. (2021). The role of investor attention in predicting stock prices: The long short-term memory networks perspective. *Finance Research Letters, 38*. https://doi.org/10.1016/j.frl.2020.101484

Zhang, D., & Lou, S. (2021). The application research of neural network and BP algorithm in stock. *Future Generation Computer Systems, 115*, 872–879. https://doi.org/10.1016/j.future.2020.10.009. Retrieved from.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. Retrieved from *Journal of Accounting Research, 22*, 59–82 https://www.jstor.org/stable/2490859.

Zoricák, M., Gnip, P., Drotár, P., & Gazda, V. (2020). Bankruptcy prediction for small- and medium-sized companies using severely imbalanced datasets. *Economic Modelling, 84*, 165–176. https://doi.org/10.1016/j.econmod.2019.04.003. Retrieved from.

Zoumpekas, T., Houstis, E., & Vavalis, M. (2020). ETH analysis and predictions utilizing deep learning. *Expert Systems With Applications, 162, 113866.* Retrieved from https://doi.org/10.1016/j.eswa.2020.113866.